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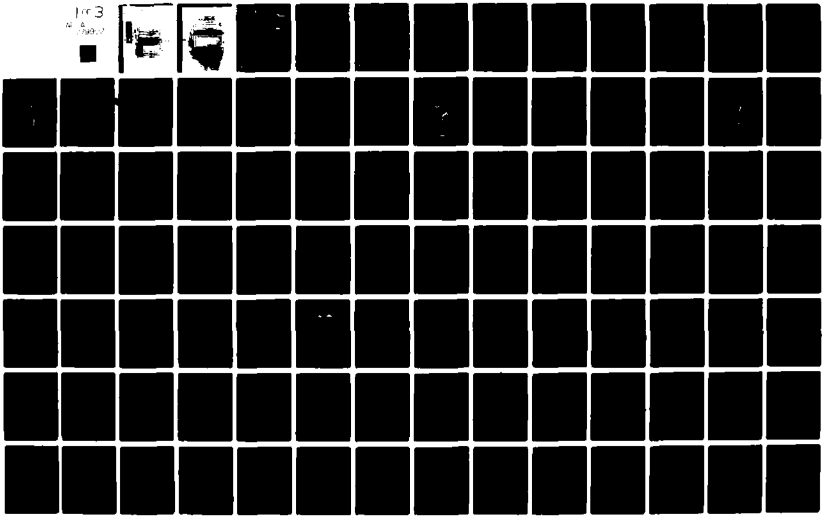

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This report examines the training characteristics of the Ground Controlled Approach (GCA) radar controller, the Landing Signal Officer (LSO) and the Air Intercept Controller (AIC). The expert and novice, in respect to these three tasks are contrasted in terms of their relative skills. The novice is characterized as a controlled serial-processing system, unable to effectively perform in a concurrent task environment wherein the tasks —— Cont'

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20. ~~(continued)~~ compete for the same pool of central resources. The expert on the other hand, is characterized as a resource efficient system capable of preprocessing and automatic responding. Several areas of basic research are reviewed in search of a set of technologies with which an instructor model, resident in an automated speech-recognition based training system, might be designed. Research in cognitive processing limitations and components are examined in some depth along with recent developments in intelligent knowledge-based computer assisted instruction (CAI). The result is an outline of the characteristics of a prototype instructor model. Some of the technologies incorporated in the prototype are insufficiently developed along the lines of the three aircraft controller tasks and thus further research and development (R&D) is required for implementation. Finally, recommendations for R&D and the dissemination of information are discussed.

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SECTION I

INTRODUCTION

Currently development programs at the Naval Training Equipment Center (NAVTRAEQUIPCEN) have been concerned with the design of automated training systems using a computer speech recognition technology. This technology may hold a great deal of promise for the automated training of tasks wherein speech is the primary mode of response. In the development of these systems, computer models of instructor behavior have been created. These models, similar to human instructors, take as input the verbal responses of the student. The instructor models must process this information, relative to the ongoing tasks required of the student, and make ational real time instructional decisions. In the instructor model, which is the control logic of the system, lies the success or failure of the automated training system itself.

Recent developments in basic research programs show promise in enhancing the capabilities of present instructor models. This would include developments in intelligent knowledge-based training systems as well as basic research in cognitive processes, and the representation of knowledge. The sections to follow will review these recent developments in basic research with the current designers of automated training systems as an intended audience. In an attempt to facilitate a crossfeed of information between the basic and applied researchers, a review of the primary characteristics of the speech-based task will also be provided with the basic researcher as an intended audience.

In the first section to follow, three exemplary speech-based tasks, the training of which is soon to be automated, are described. The descriptions are only brief introductions designed to feature the cognitive implications of training to be discussed later. References are given for the reader desiring more details on the tasks. Following the brief introductions to the tasks, their common features are discussed along with certain observable differences between the novice and expert which have implications for training.

Recent developments in basic research which could impact the design of the instructor model are reviewed in the third section. Technological achievements supported by the Office of Naval Research (ONR) were featured when relevant, for programatic continuity. The areas of basic research reviewed were a result of an analysis of the three exemplar tasks. In that analysis, it became apparent that the dominant common characteristic of speech-based tasks was the time-sharing component. Thus the research on information processing limitations and stages is reviewed fairly extensively. Perceptual and motor learning research is also discussed briefly as they are major components in two of the speech-based tasks. Recent developments in computer-assisted instruction (CAI) are also reviewed in terms of their possible implications in training system designs for speech-based tasks. The speech-recognition technology itself was not reviewed as our major concern was with the design of the instructor model.

In the fourth section, the characteristics of an ideal instructor model were considered. The characteristics included were based on both the availability of specific technologies identified in the reviews, as well as the needs identified in the analysis of training requirements. The fifth section deals with gaps in technology which preclude the immediate development of our prototype instructor model.

The discussion centers around the practical considerations of filling the technological gaps, part of which involves the crossfeed of information between the basic and applied researcher.

The three exemplary speech-based tasks presented were selected as a result of their current programs for automation, directed by the Naval Training Equipment Center. In all three, the student is being trained in some form of air traffic control. The student must learn to process visual and auditory information rapidly while making verbal advisories, to the aircraft involved. The first two controllers provide for aircraft control during landing operations. The third provides control during tactical maneuvers.

SECTION II

CURRENT AUTOMATED SPEECH BASED TASKS

GROUND CONTROLLED APPROACH RADAR CONTROLLER

The Ground Controlled Approach (GCA) term refers to both ASR (Aircraft Surveillance Radar) and PAR (Precision Approach Radar) control. The present context however, is only concerned with PAR training although the acronym GCA is often used. The GCA (PAR) controllers consist of enlisted personnel whose primary responsibility is that of monitoring and advising aircraft on their final approach until touchdown. Their task is to monitor a radar scope consisting of a divided display, and make frequent (almost continuous) advisories, according to rigid vocabulary and procedural constraints.

Figure 1 shows an example of a PAR display. The two lines (cursors) with the hashmarks represent the glide-slope, the top cursor (elevation) representing vertical position, and the bottom (azimuth) representing lateral position. The hashmarks themselves represent miles from touchdown. The more prominent hashmark is the five mile marker. The aircraft itself is represented as a radar return (target) with a short trail. The purpose of the trail is to give the controller direction of motion information as each radar sweep will only give static position of the aircraft at the time of the sweep. As can be seen, the aircraft (target) is just inside the two-mile mark, coming up on the glide-slope, but drifting off to the right.

The phraseology that would be used to advise the pilot depends in part on the point at which the target intersects the cursor. Figure 1 exaggerates the size of the target

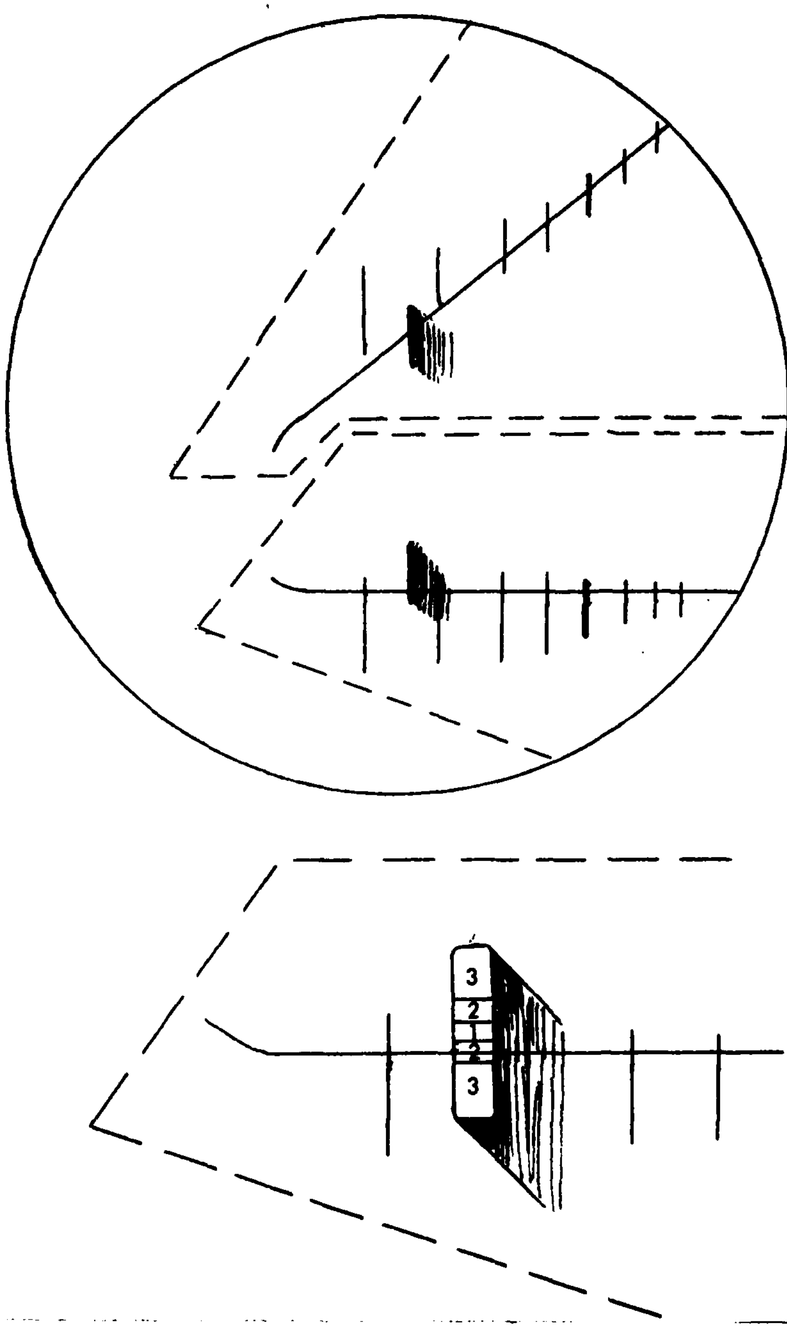

Figure 1. Characteristics of the PAR Display (Top)
Enlargement of the Azimuth (Bottom)

to illustrate that it is broken into zones. An intersect in zone number 1 is depicted as being on course, while the adjacent zones (2) are cues for the use of the adjective "slight" as in the statement "slightly right of course." Should the target be far enough to the right of the cursor that there is no intersect, the statement would be "well right of course."

In addition to the terminology pertaining to the azimuth, there are specific elevation messages which are either statements of trend or position. Further, there are assigned headings to give as well as other control messages. These are summarized in Table 1 (Grady and Hicklin, 1976[1]). Position and trend messages must be alternated and phrased in such a way as to depict movement to the pilot. Table 2 gives the legal relationships between trend and position messages. Grady and Hicklin (1976)[1] also cite the following additional rules governing glidepath trend messages:

(1) Trend must be given between two different glidepath position messages.
(2) Trend may not be given between two identical glidepath position messages.
(3) Two trend messages must be separated by a glidepath position message.
(4) The trend message must be the correct one given the position message which follows it as shown in Table 2.

The following rules are applied to course correction messages:

(1) Course corrections may be given once the aircraft is on final approach.

TABLE 1. RADIO TERMINOLOGY

Glidepath position messages:

Approaching glidepath
Well above glidepath
Above glidepath
Slightly above glidepath
On glidepath
Slightly below glidepath
Below glidepath
Well below glidepath

Glidepath trend messages:

Coming down
Going below glidepath
Going further below glidepath
Coming up
Going above glidepath
Going further above glidepath

Course messages:

Assigned heading _ _ _
Turn right heading _ _ _
Turn left heading _ _ _

Other control messages:

Begin descent
__ mile(s) from touchdown
Wind calm
Wind _ _ _ at _ _
Cleared for low approach
At decision height
Execute missed approach

TABLE 2. TABLE OF LEGAL TREND MESSAGES SCORED WHEN THE NEXT GLIDEPATH POSITION IS SPOKEN

Legal Trend Messages		Next Glidepath Position Message
Upward Trend	Downward Trend	
Going further above glidepath	- - -	Well above glidepath
Going further above glidepath	Coming down	Above glidepath
Going above glidepath	Coming down	Slightly above glidepath
Coming up	Coming down	On glidepath
Coming up	Going below glidepath	Slightly below glidepath
Coming up	Going further below glidepath	Below glidepath
- - -	Going further below glidepath	Well below glidepath

(2) Outside three miles from touchdown, the minimum course correction is five degrees and the maximum is ten degrees.

(3) Within three miles from touchdown, the minimum course correction is two degrees and the maximum is five degrees.

(4) Heading digits and direction of the correction must correspond.

(5) Direction of the turn must be correct; i.e., when the aircraft is right of course and heading away from the centerline, a left turn would be correct.

(6) Assigned heading messages may be given at any time but the heading must be identical to the last heading given.

This short description of the GCA controller's duties is by no means exhaustive. The controller also has other responsibilities such as wind and clearance messages, etc. A more detailed description of the task requirements may be found in the GCA-CTS Student Guide under development by Logicon at the time of this writing.

As can be seen by looking at the GCA controller's responsibilities, the phraseology and rules of production are well documented and standardized. The limited vocabulary and definite structure are an advantage when considering automated training as noted by Feuge, Charles and Miller (1974)[2]. At the time of this writing, a trainer referred to as the Ground Controlled Approach-Controller Training System (GCA-CTS) has been produced and is being delivered to the government for further test and evaluation. Breaux (1976)[3] describes the initial laboratory version of the GCA-CTS while Barber, Hicklin, Meyn, Porter and Slemon (1979)[4] document the current version of GCA-CTS.

LANDING SIGNAL OFFICER (LSO)

The major role of the Landing Signal Officer (LSO) is again that of aircraft control. In this case, the LSO is not only an officer, but also an experienced pilot. His duties include the training of pilots, and new LSOs as well as the control of aircraft landings aboard a carrier. He is selected from a pool of pilots during either his advanced pilot training or his first fleet squadron tour of duty.

His selection is said to be based on: motivation, aviation ability, and potential as an instructor. A detailed description of the LSO's role can be found in a report by Hooks, Butler, Gullen and Petersen (1978)[5].

Current training of LSOs exists in three phases. The first phase consists of nine working days of formal training at Pensacola, Florida. It consists of classroom sessions and field trips to the extent possible. It emphasizes the theory of LSO operations and information regarding shipboard equipment and systems with which the LSO must interact. The second phase of training involves skill development. Here the trainee gains experience with observation and control of Field Carrier Landing Practice (FCLP) operations. The third phase involves the observation and control of air wing aircraft aboard ship. The type of instruction received in these last two phases is primarily that of apprenticeship to senior LSOs, is informal and largely unstructured. The length of time spent in training is hard to define in that on-the-job training (OJT) as defined in the third phase, continues on indefinately. The rate of training is dependent on OJT opportunities.

The dependence of training on OJT opportunities has created a severe man-power shortage. Recent decreases in carrier deployment (Hooks, et al., 1978[5]) have been cited as the causal factor in observed LSO shortages and reduced proficiency levels on the part of experienced LSOs. This reduction of carrier landings has had several effects. It has caused decreased availability for: the required OJT needed for LSO training, the re-establishement of skills for the LSO returning from a non-LSO tour of duty, the opportunity to assess LSO performance, and the enrichment experiences that come with exposure to a great variety of carrier landing situations. An additional problem arises as a result of the pilot's decreased availability to practice with carrier landings. This reduced proficiency noted in the pilots' skills places increased demand on the LSO's performance. For these reasons, the training of LSOs has been judged a likely candidate for automated training.

Like the Ground Controlled Approach Controller, the LSO's job is a complex cognitive task. Hooks, et al. (1978)[5] break his responsibility of the control of aircraft landings aboard ship into four elements: (1) assess aircraft approach, (2) assess recovery conditions, (3) direct pilot actions, and (4) advise superiors of recovery feasibility, efficiency, and safety. To this end, the LSO is situated on a platform located to the side of the ramp and just aft of the arresting cables. Figure 2 shows a stylized diagram of the view from just above the LSO platform. From this platform, the LSO must make visual judgements of the aircraft's vertical and lateral positioning relative to range from carrier and an optimum glide slope. To communicate to the pilot, the LSO holds a communication cradle not unlike an ordinary telephone receiver to his ear.

Figure 2 gives some idea as to the fine perceptual judgments the LSO must make, specifically when the aircraft is some distance from the carrier. After the final turn, the LSO acknowledges receiving control and begins making judgments as to the aircraft's position. The stylized trail depicting the trajectory of the aircraft is to illustrate gross deviations from the glidepath. Note that in the distance, even gross deviations by the pilot would

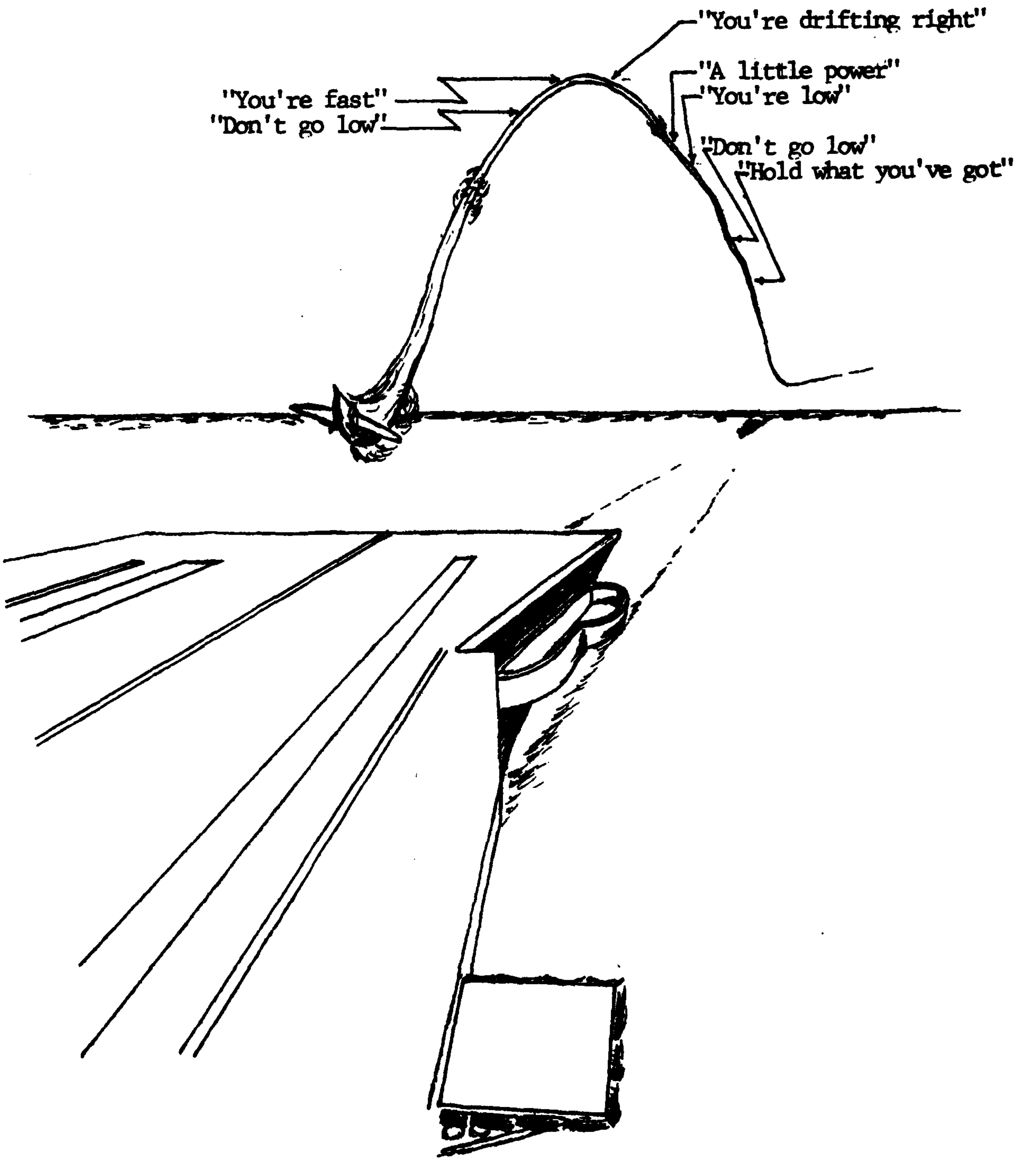

Figure 2. View from Above the LSO Platform

require fine perceptual judgments on the part of the LSO. Precise elevation discriminations relative to an "internalized standard" glideslope would be difficult for the novice, to say nothing of judgments of lateral position. Example advisories are shown in the figure to illustrate the type of vocabulary used. Only samples of a standardized vocabulary are shown, but unlike other types of controllers, the LSO may use nonstandard phrases.

The visual conditions under which the LSO must work are less than optimal. There is usually a haze over the seas making distal objects hard to see. The aircraft, at the beginning of the glide slope will appear as a small spot in the haze with little apparent movement. The horizon may or may not appear as well defined through the haze. The deck and LSO platform will be in motion depending on the sea conditions. According to Hooks et al. (1978),[5] the LSOs report that they attend to changes in aircraft pitch attitude, acceleration and engine thrust changes. The cues for engine thrust changes are auditory and visual (smoke). In addition to attending to the aircraft itself, the LSO has available other aids such as the Pilot Landing Aid Television (PLAT) for line-up indications and the SPN-42 radar data readouts for glide slope, line-up and speed indications. Because of the attention demands a backup LSO must attend to these other aids and verbally report to the LSO in charge.

In addition to the auditory cues the LSO receives from the aircraft itself and the advisories from the backup LSO, he will receive communication from the pilot and other support personnel. In addition to his hand-held voice transmit-receive device, he holds a device for activating waveoff and cut lights called a "pickle." Other work station devices include the MOVLAS control, a hand operated lever for signalling perceived glide slope positions of aircraft, and console-located intercom switches for intercommunications to Air Boss, etc.

There are several variables which would effect the LSO's performance. The deck motion (roll, pitch, heave, and yaw) will effect position cues relative to the aircraft, horizon and plane guard destroyer following the carrier. Visability itself may be attenuated by haze, and ceiling, and of course night landings in which the only cues are the lights of the aircraft relative to the lights of the destroyer. Voice communications with the pilot are received in a background of other transmissions over the same frequency as well as verbal calls from support personnel on the platform. Additionally the type of aircraft will vary in terms of speed and maneuverability as well as varying in fuel state and emergency conditions (engine failure, hydraulic system failure, etc.). Needless to say, the LSO may at times experience tremendous information load. Hooks et al. (1978)[5] report that the major determiner of an LSO's performance rating is his ability to perform under pressure.

AIR INTERCEPT CONTROLLERS (AIC)

Another challenge for automated speech recognition based training systems is the training of Air Intercept Controllers (AIC). While also involved with air traffic control, the AIC's role is that of directing an intercept aircraft in a combat situation to destroy an enemy aircraft. Unlike other air traffic controllers whose job it is to keep aircraft a safe distance apart, the AIC's role is that of bringing controlled aircraft together safely for the purpose of intercepting a target. There are obviously great risks involved when calculating the interception of high performance aircraft. Multiple aircraft will be assigned one target to attack sequentially from different angles. The AIC is dealing with split-second decisions and motor responses in the controlling of these aircraft displayed on a complex monitor. His controller phraseology is more diverse than that of the GCA and his performance and learning demands are more complicated. The AIC is generally concerned with mission-oriented control and may be stationed on board a ship somewhere near the mission zone.

The more recent training advances have not yet impacted the training of AICs due to its complexities although the need for an improved training situation has been indicated. The fleet's readiness requirements become more and more difficult to meet due to high cost and low availability of live-air training. It would be advantageous to have a training system capable of supplementing live-air training adequately.

AICs are made up of officers and senior enlisted personnel trained at the Fleet Combat Training Centers, (FLECOMBATRACEN) located in San Diego. A class consists of students who work together for six weeks of training. The first three weeks consist of classroom instruction and simulated air control. This training is supported by a training system developed in the 1960s referred to as Tactical Advanced Combat Direction and Electronic Warfare (TACDEW). The second three weeks of training involves the use of real aircraft and pilots. FLECOMBATRACEN averages 25 training flights per day, but the distribution of the flights is often awkward for efficient training. Instructors have indicated a desire for a training system capable of switching to a synthetically generated environment during lag-time between live intercept missions.

Prior to 1977, the training of AICs was of a more traditional method requiring the mastering of a technical manual and proper button-pressing sequence. Now the course is task-oriented beginning with easy tasks and progressing to the more difficult. Each step in the job is explained and the equipment is discussed in terms of its role in that assignment. This change in philosophy of training has been beneficial to both the instructor and the student, but many needs still exist in the efficient training of AICs. FLECOMBATRACEN and NAVTRAEQUIPCEN have proposed the possibility of a large-scale training device to support AIC training in the 1980s which is directed at alleviating many of the training problems (Grady, Hicklin, and Miller, 1977[6]).

A sketch of a possible training device similar to that proposed by Halley, King, and Regelson (1979)[7] is shown in Figure 3. Consoles differ between ships so this one is not necessarily representative of all the different types of consoles. It will serve to demonstrate an apparatus with which an AIC must interact to achieve the required intercept. Centered on the console is the display of all raw radar return. Superimposed on this is a display of a limited amount of computer graphics or symbology. The numerous control panels around the radar display regulate various functions such as the expansion or off-set of the radar display, the building of symbology on the display, the locking on of the symbols on the radar display, etc. A track ball controls the position of a tab (similar to a cursor on a CRT)

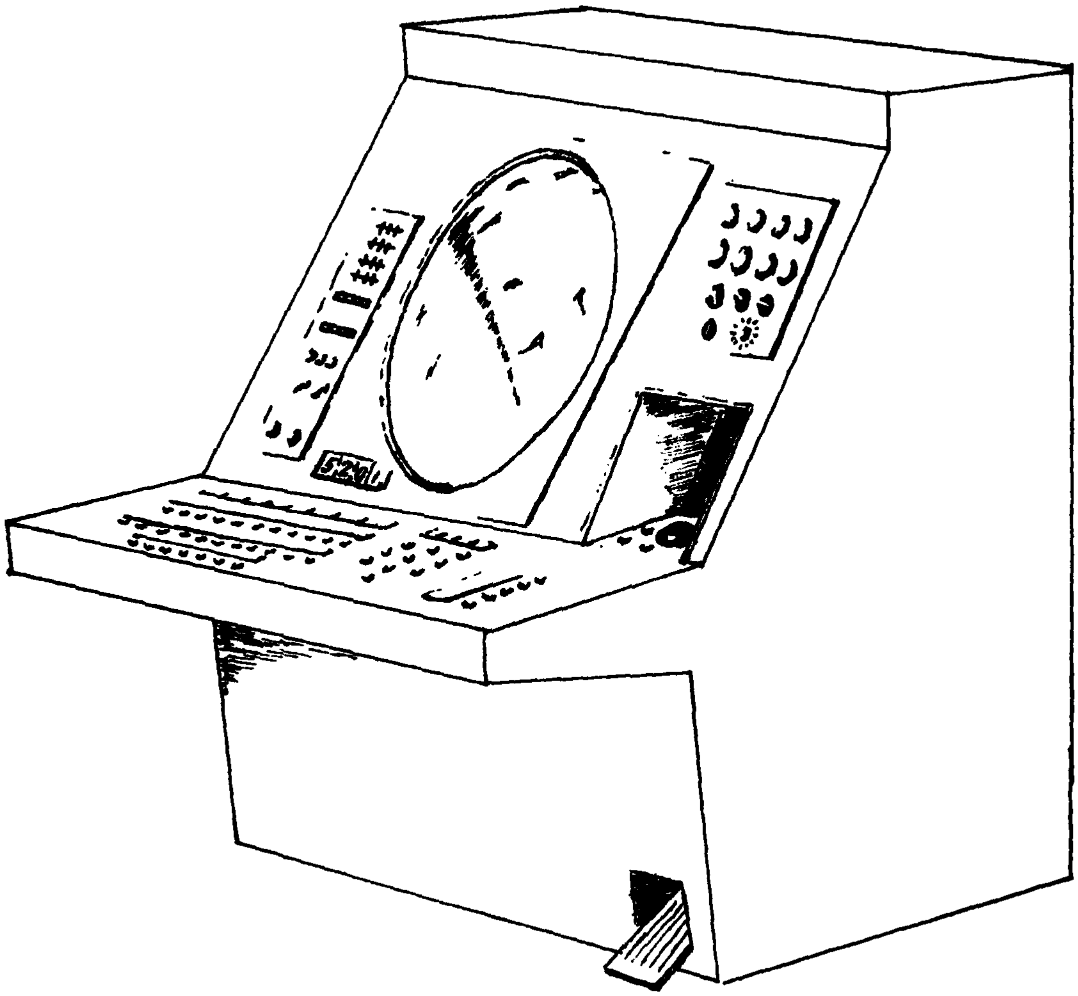

Figure 3. Exemplar AIC Work Station

on the display. A head set is worn which is open to all transmissions on a given frequency and a foot control is used for keying the mike. A number entry pad is used for the entry of data and there are numeric displays to be monitored.

Before assuming control of the monitor, the AIC attends a briefing which will inform him of the nature of the on-going or anticipated mission(s) or training maneuvers, and various other pertinent information such as weather conditions, topographical problems such as mountains, etc. He spends some time then actually viewing the radar return, listening to transmissions and generally getting an overall impression of what kinds of return on the display are static (mountains) and what are dynamic (aircraft). Upon assuming the responsibility of the controls, the AIC must identify aircraft entering his scope by means of a check-in procedure with the aircraft. The Combat Air Patrol (CAP) possess a transponder which continuously squawks a code. The AIC "challenges" the new return on his screen through a series of motor responses and identifies the code the CAP is squawking by a display on the lower left-hand section of the console. He then procedes to build a CAP symbol and then "hooks" the symbol so that the computer will continue to make calculations for that assigned symbol. By building symbology in this manner, he is allowing the computer to keep track of the interceptor in a rather complex display. This is followed by the entry of three multi-digit codes on the number entry pad, and the depressing of the order-send button. The check-in is then completed with a radio check by the AIC.

When a "bogey" (unidentified aircraft) is detected, the AIC communicates with his assigned aircraft to vector him to the nearest point of intercept. He must then continue to provide the pilot updated information as to the bogey's bearing, range, track and ground speed. Sudden changes in the bogey's parameters require new vectors to be calculated and then reported to the pilot. While plotting and controlling the intercept, he must be constantly aware of the range, bearing, track and ground speed of other aircraft in the vicinity of the controlled aircraft. He must also be verbally responding to communications from the pilot(s).

Although this is obviously an abbreviated synopsis of the AICs multidimensional tasks, we can nonetheless gain some insight and appreciation for the complexity of the training situation. An expert AIC related in a personal communication some of the difficulties he encountered in training. In a general sense, mastering the automated system and all the manual inputs required to accomplish multiple intercepts coupled with the mental and verbal demands was very difficult until some state of automaticity was reached. In a little more detailed sense, he identified six difficult areas of mastery: (1) properly setting up the scope initially, (2) properly identifying all the "players," (3) punching in the correct responses or buttons of his scenario to accomplish the mission without taking his eyes off the scope, (4) the pacing demands relative to the speed of the target (usually very fast, e.g. reconnaissance aircraft traveling over 2000 mph), (5) understanding the computer programs in the system and how to use them to accomplish the goal, and (6) the phraseology.

COMMON FEATURES OF THE THREE CONTROLLER TASKS

The three controller roles just outlined, represent the beginning point for automated-speech-recognition-based training technology. All three of these job roles are currently experiencing a man-power shortage in the Navy, and could benefit from automated training. Present training methods vary for the three jobs but all begin with a school designed to introduce the students to their subsequent duties. As Nowell (1978)[8] points out, there is limited training time associated with these schools. There may be an instructor shortage as in the case of training AICs, and the instructional cost per student is quite high. Once the student leaves the school, OJT opportunities for further training may be on the decline as reported by Hooks et al. (1978)[5] in the case of LSOs.

All three training programs share a common mode of response--that of speech. The speech requirement may serve as a task dimension that will set these roles apart from other military roles. As one might surmise, if the student's response mode is verbal (a mode which is quite slow), other resources could simultaneously be required. A point which we will attempt to make, will be that these tasks require the student to perform various processing functions (and possibly motor responses) concurrently with speech production thus comprising a multi-task situation.

Now a second characteristic of these tasks, not unrelated to the multi-task feature, is that a major portion of the tasks performed by controllers are event-driven, meaning that the pace of the task is controlled by external events. It follows from the nature of multi-task situations that the pace of events may at times challenge the student's resource capacities. Thus the objective of an instructor model in these situations, would be to not only build knowledge structures within the student using CAI technology, but also to develop certain processing skills via adaptive training technology to allow for effective resource utilization.

The primary stimulus mode for all three tasks is visual with intermittent verbal inputs from pilots and possibly support personnel. The visual input may be of the complexity that it requires the training of perceptual and visual search skills. All visual cues are above threshold with possibly some minor exceptions. As in the case of visual displays, the complexity may foster divided as well as focused attention deficits. More will be said about this later as the controller's tasks are analyzed in more detail.

The ability to process information from a complex display, select and execute a verbal response in seemingly parallel functions, seems to be at the heart of the controller's skills. Hooks et al. (1978)[5] report that the major determiner of an LSO's abilities is his ability to perform under pressure without getting "flustered" or "confused." Stated in other ways, this becomes his ability to process and respond accurately under heavy information load. The ability to process efficiently large amounts of visual (and/or auditory) inputs concurrently with speech production at a rapid pace, is the major difference between the novice, and the highly skilled controllers. These are the characteristics of the controller's tasks which an automated-speech based instructor model must address.

The core of an automated training system is the <u>instructor model</u>, by which we mean the control logic in the system which in many ways may emulate a human instructor. In using the human instructor as a point of departure, we would note that the instructor is usually an expert in the field in which he instructs. Having been a student once himself, he may have insights as to what he was like as a novice, what he is like as an expert, and some opinions as to the process which transformed him from a novice to an expert state. He can then use these insights to guide his instructional decisions which he makes during the instructional process. These insights and past experiences are incorporated into his internal logic as it were. He in effect, understands the process through which the student is going.

Before creating an instructor model, we must understand: the expert, the novice, and the technical difference between the two, in a way that will allow us to deduce the control logic for an automated trainer. Since the developers of training systems are usually not subject matter experts (SME), the development process is usually preceded by a period of preparatory investigation, sometimes called task analysis. Usually a task analysis involves collaboration between SMEs and the technical staff responsible for system development. Often this is merely a breakdown of the task into subtasks, duties and skills which the student is to acquire by interacting with the system. This level of analysis may not imply specific training techniques to be used.

In the sections to follow, we will present a task analysis based on current basic research issues in <u>process</u> and <u>structure</u> which is to lead to the beginning of an instructor model for automated speech recognition based training systems. It is to be kept in mind that the purpose of the analysis model is provocative in nature. Ideas and positions are proposed which may remain unvalidated until empirical support is found. We will propose that the skills and abilities of the expert ought to be analyzed in some detail, and contrasted with an analysis of the novice's inabilities, errors, omissions, etc. These contrasts should be done in such a way as to suggest certain training techniques, and instructional strategies. For purposes of the present paper, the analyses of the controller tasks were carried out using the applied technical reports cited, interviews with students and instructors, and the basic research literature (concentrating where applicable on the efforts supported by ONR).

PRELIMINARY OBSERVATIONS OF THE EXPERT AND NOVICE

The present authors have followed the development of GCA-CTS somewhat since its inception, and have interviewed the chief warrant officer monitoring the development. This individual was not only an "expert" controller, but was also the person in charge of PAR instructors. In trying to describe his behavior during an approach, he found introspection difficult as so much of it, in his words "is automatic." He added however, that the students do not reach this "automatic" level in the short two weeks of PAR training in which the training system is to be utilized. In this two week training period, the students would receive only 12-15 hours of actual practice on the display. Following the formal training period, they would receive another 160 hours or so of OJT.

In describing the characteristics of his proficiency, the expert stated that he "does alot of looking ahead." His experience allows him to anticipate what the next event will be. Upon interrogating the expert further, he described the "looking ahead" as an anticipation of a response rather than a perceptual anticipation. With his experience and the information he "carries in his head" (such as: the type of plane, wind direction and velocity, thermals, etc.) he is able to anticipate what the target will do next on the display and what his probable next call will be.

The PAR students present quite a different picture than the expert. We had only limited opportunity to observe two students at the beginning of their training on the scope. At this time the display was simplified with the removal of the elevation cursor leaving only the azimuth to which the student was to respond (see Figure 1). Even with the simplified display, the most common errors with the beginning student were caused by his inability to process the information rapidly enough.

Listed below are examples of eight types of errors which were observed. For the first example, it was found that students could not compute and give course headings fast enough. If the verbal responses were to be:

TURN RIGHT HEADING..ONE..FIVE..FIVE.....SIX..MILES FROM..

the student would respond:

TURN RIGHT HEADING..ONE....FIVE.........FIVE.........SIX

Since the level of speech-recognition technology used at the time did not have connected-speech capabilities, the students were required to make short pauses between phrase segments and numbers. The beginning student however, was observed pausing between numbers, presumably performing mental calculations, for a much longer duration than required by the technology. These "concentration pauses" had several effects. By the time the last digit was given the pilot was late in executing his turn. This meant that additional corrections were then required of the student to bring the pilot back on course.

A resulting error was that the pauses would cause him to miss the next call such as giving the pilot his range to touchdown. The students stated that they could tell they were missing the range call, but "the next call was required to get the pilot on course, and there simply wasn't enough time." Thus the first two types of errors are related, those being inevitable pauses and the resulting missed calls.

A third type of error was that the headings given were sometimes inaccurate. When the students were asked to introspect on their thought processes in computing the headings, they responded that they tried to visualize the aircraft (as it intersected a line to the runway) as if they were looking down on it. Knowing the aircraft's present heading (an estimate), and the runway heading (e.g. 150° and 160° respectively), they then used this visualization to determine that a right turn was needed with a ten degree correction. Further, they know that at this point in the approach the corrections should be given in five degree units. Finally they would conclude that the first of the corrections should be a right turn to 155°. The process they describe would be assumed to be quite time consuming whereas the expert states that he is not really aware of any thought processes, he just does it--rapidly.

A fourth characteristic of the novice may be referred to as excessively long dwell times. He will fixate on some portion of the display (presumably while he is slowly processing the information in order to make a response) and neglect other portions of the display. As an example, when both the elevation and the azimuth are present on the display (see Figure 1) the student may dwell on elevation call(s) and neglect the scanning of the azimuth. The result of course is that the pilot may slowly drift undetected off course.

A fifth characteristic is that the student will give a correct call but in the wrong form. It will be recalled that the PAR controller's calls must be made within rather strict verbal guidelines (see Tables 1 and 2). Thus the student may transmit the incorrect phrase, "How do you read me?" when the correct phraseology should have been, "How do you hear me?"

The students report an additional phenomenon we will term the sixth characteristic. They report that they will lose certain information that they are supposed to "carry in their heads" (presumably short-term memory) for subsequent use. For example, just before the handoff, (when the student takes control of the aircraft from another controller) the aircraft's current heading is transmitted. When he finally takes control and is required to compute a course correction, he discovers to his dismay that he can't remember the aircraft's current heading from which he must compute the change.

A seventh observation was that when processing load increases, the student's voice quality degrades. The quality is of course important for controller communication, but even more troublesome for the automated-speech-based training system is the fact that changes in voice quality preclude the system from identifying the transmission. If, for example, the student is getting behind in his calls, he becomes confused as to how he should handle the situation. He may begin to speak softly, change intonation and pause in awkward places in the phrases. His hesitancy may be manifested by his inadvertently mumbling "Uhmm..." in place of designated pauses. This creates an input such as "GOING UHMMFURTHER...ABOVEUHMMGLIDEPATHUHH...." which the system cannot recognize.

A final error is described by the student as "not knowing what to do." He will make a wrong call and then display surprise that it was wrong or he will panic during an approach, turn to his instructor, and ask,"What am I supposed to do in this case?" An example situation is when an aircraft appeared on the display on a heading quite discrepant (e.g. 210°) from the approach heading of 160°. The surprised student attempted to issue a course correction of five degrees followed by a second course correction of five degrees and so on. In the middle of his second advisory the student realized that the target would intersect and surpass the cursor by the time he could issue enough course corrections in five degree units. He began to hesitate in his speech and stammer somewhat as he helplessly watched the aircraft fly off the display. It became apparent after discussing it with his instructor that he simply did not have the knowledge about how to handle that situation.

These eight types of errors, though not exhaustive serve to illustrate the initial problems of the novice. The last type of error we would like to refer to as a <u>structure</u> problem. By structure we mean in short, "knowledge," although the concept of structure will be developed more fully in the sections to follow. In this case, errors are committed, or maybe a response was omitted, because of a lack of "knowledge" (structure) on the student's part. Predictably, if the student had read and reviewed his manual before getting on the trainer, we found few errors of this sort. Only if the manual had not been reviewed did the student make many errors from the standpoint of a lack of knowledge.

Most of the errors we observed, we will refer to as processing errors. We propose that the first seven types of errors committed, were caused by the slow rate of processing on the part of the novice. The students could tell us after an approach, the responses that should have been made, so we assume they possessed the "knowledge." They would comment that "there simply wasn't enough time" or "too many things were happening at once." Thus in the present analysis, we would propose that the first seven characteristics of the novice are caused by processing limitations. The longer-than-required pauses in speech were caused by the student not being able to speak and think concurrently. The student's slow rate of processing causes him to fall behind in his event-driven task which in turn causes him to miss some of the calls. Two other types of errors, those of incorrect phraseology and incorrect heading computation, we will argue are often the result of incomplete processing. That is, because of the paced nature of their task, the students feel that they must respond though they feel "hurried" and have not had enough time to fully process the response. It was felt that the excessively long dwell times were similar in nature to the pauses in speech--that of not being able to attend to additional elements of the display while processing. The loss of information from short-term storage may also be due to excessive processing load inhibiting the rehearsal or the recycling of the information. Finally the degradation in speech quality could logically be due to the student's inability to process and speak simultaneously when the load becomes heavy. Thus in observing the novice, and interviewing the expert, we concluded that any instructor model for aircraft controller training systems would need to be concerned with the effect of training on processing skills in addition to the building of knowledge structures. The inclusion of process considerations makes the automated speech-based systems unique from the more traditional CAI approaches.

SECTION III

RECENT DEVELOPMENTS IN BASIC RESEARCH

The usage of verbal reports from both the expert and the novice can yield valuable insights on training methods and instructional logic for incorporation into a subsequent instructor model. Reliance on verbal reports, however, may be quite limited. Neither the expert controller, nor the novice are familiar with the terminology found in a cognitive science. One gets a definite feeling when questioning the students that the questions are often leading, and the responses often reported in a form that fits our own internal schemata. In our thinking, the validity of the verbal reports should be treated as tenuous and only used as a point of departure for further verification. This subsequent verification would quite naturally follow from any empirical data we might be able to find. In the sections to follow, we examine the basic research literature to see what it has to offer in the development of an instructor model. We will start by choosing to make a distinction between process and structure as their requisite training technology would differ.

PROCESSING LIMITATIONS

A major difference between the expert and the novice is that the expert seems to be able to simultaneously handle multiple inputs, hold information in memory, process the information, and select the next response concurrent with the execution of a verbal response. The novice, on the other hand, seems to be analogous to the person who can't walk and chew gum at the same time. The novice seems to be held back by a limited central processing capacity. The concept of a limited capacity can be traced back to the attention literature of the 1950's and 1960's with the single-channel model of Broadbent (1958)[9] and the filter position of Treisman (1960)[10] as exemplars. These early models put the source of the proverbial bottleneck on the attention stage of the process. Subsequently, Deutsch and Deutsch (1963)[11] proposed that the bottleneck occured later during the decision or response stages. Shiffrin (1976)[12] continued this notion referring to the concept as capacity limitations, while others refer to it as resource limitations.

Kahneman (1973)[13] proposed a resource competition model that assumed that all cognitive tasks draw from the same pool of limited resources. Thus, if a particular task demands a large share of the resources, there will be little left over if a second task is required. This reasoning led some researchers (e.g. Posner and Boies, 1971[14]) to use a reaction time (RT) probe as a measure of the processing demands of a particular task. The idea was that as the resource demands of a primary task increased, the longer the RT to the secondary probe task. The benefit of this approach could be that different primary tasks (or the same primary task at different stages of learning) could be assessed in terms of their relative processing demands by their probe RT measures. Some reservation in this methodology for assessing the demands of primary tasks lies in the findings that visual and auditory probes lead to different patterns of results (Schwartz, 1976[15]) while different responses to the probes (manual vs. vocal) also lead to different results (McCleod, 1978[16]).

A second methodology of interest, termed the "secondary task paradigm" was developed and is discussed by Kerr (1973).[17] Here the subject is given two concurrent tasks. One is designated the primary task and the subject is told that a certain level of performance on this task must be maintained. The other task, deemed the secondary task, is allowed to fluctuate in performance level. These two tasks are naturally assumed to compete for the same central resources. As the demands of the primary task are increased, the performance of the secondary task declines while the primary task's performance remains invariant. Thus the secondary task is used as a measure of the processing demands of the primary level.

In the past, two positions have been taken in these dual task situations. One view (Kahneman, 1973[13]) is that these (vague) limited resources may be viewed as a pool of "effort" which may be allocated among tasks. This common undifferentiated pool of "effort" is drawn upon from essentially all tasks, no matter how diverse. The second view (Posner and Keele, 1970[18]) is that some tasks compete for the same resources while others do not. Kerr (1973)[17] concluded that two very different categories of what was referred to as mental operations may not require the same central mechanism at all and may be executed in parallel (such as encoding and executing a movement to a physical stop). This parenthetical example would of course be pertinent to a segment of the AIC task, that of visual encoding of the display cues, during the execution of button pressing responses. Other of Kerr's categories, she concedes, do compete and interfere with each other.

More recently, ONR has funded some projects which looked at the resource limitation problem. Hunt, Lansman, and Wright (1979)[19] report additional support for the general notion of Kahneman (1973)[13] in that relatively diverse tasks showed performance decrement when combined. The Hunt, et.al. (1979)[19] report is also of interest in that "reasoning" was one of the mental operations, whereas most of the previous work utilized perceptual or motor reaction time, or short-term memory paradigms. In one experiment, Hunt, et.al. (1979)[19] used non-verbal intelligence test problems of varying difficulty level paired with a simple psychomotor task. They found the performance on the secondary psychomotor task to decline just prior to the first error on a test problem as the problems got progressively more difficult. This, of course, would have implications in adaptive training in that the secondary task could be used as a difficulty level index when error measurement on the primary task proves insensitive. These paradigms have also been used to assess individual differences in processing capacity (see Lansman, 1978[20]).

The possibility of using secondary tasks as indirect performance measurement sounds tempting, but there are further considerations. As Kerr (1973)[17] and Posner and Boies (1971)[14] point out, sometimes task A interferes with task B but not vice-versa, while sometimes two tasks don't interfere with each other at all. These findings are further used for the contention that at least one of these tasks in these situations do not require the same central processing capacity. "If they did, they both would be expected to interfere." (Posner and Boies, 1971, p. 407 [14]). As a response to this, Norman and Bobrow (1975)[21] developed their concepts of data-limited and resource-limited processes. In their view, whenever the performance on a task can be increased with a increased allocation of resources (e.g. processing effort, or concentration), then the task was said to be resource-limited. Whenever the performance level remains invariant to increased allocations of processing effort (resources), the task is said to be data-limited. Here the performance is limited by either poor signal quality (e.g. low signal-to-noise ratio) which was referred to as Signal data-limits or an inadequately stored memory representation referred to as Memory data-limits.

Norman and Bobrow[21] describe what they referred to as a performance-resource function in which task performance is related to a single hypothetical dimension of resource allocation. Figure 4 shows resource allocation functions for two tasks. As additional resources are allocated moving from point A to point B on the abscissa, performance increases on both tasks and are resource-limited at all points in that range. But as the allocation is further increased from points B to C, no further increase in task I

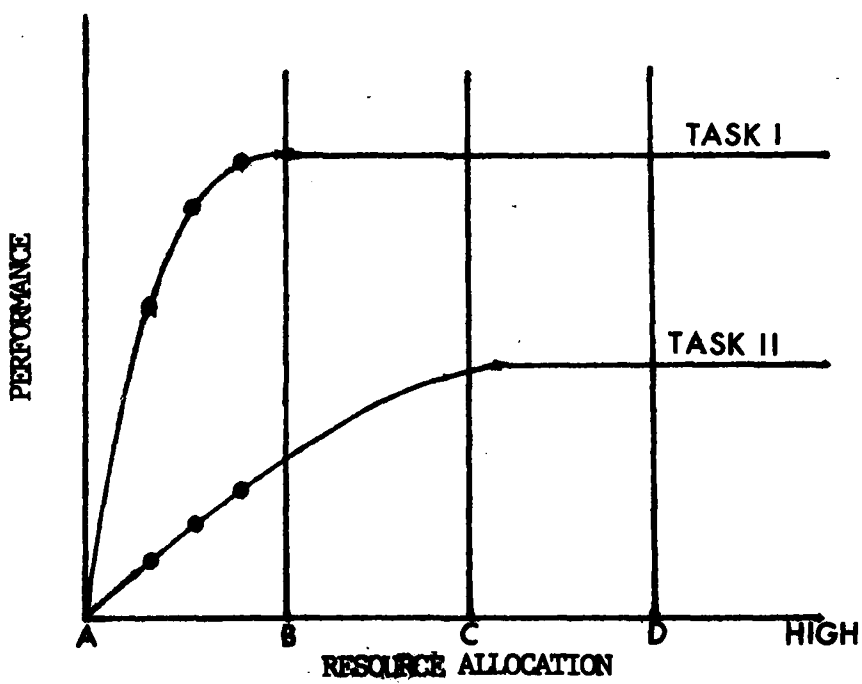

Figure 4. Two Example Resource Allocation Functions

is produced; thus task I is now data-limited while task II is still resource-limited. At point C, task II makes the transition to data-limitation. Beyond point C, further allocations of resources will not effect performance, only changes in the tasks themselves (e.g. increasing signal-to-noise ratio) will produce performance changes.

The performance-resource function shown in Figure 4 shows performance on both tasks increasing as increases in resources are allocated to both simultaneously. But the underlying assumption is that the resources are common to both tasks and limited. Thus the only way that we can increase allocation of resources to task I is to take some of the resources from task II and vice-versa. Thus in the figure, as the horizontal coordinate on the task I function moves to the right, the horizontal coordinate on the task II function would be required to move to the left. In the region from A to B, movements of the horizontal would also imply movements on the vertical. As can be seen, increases in performance on one task due to increases in resource allocation would cause decreases in resources and possibly decreases in performance on the other task. The actual relation to performance would depend on the region of the abscissa included in the investigation.

Resource allocation functions are largely hypothetical since, as Norman and Bobrow[21] point out, the problem would be in the control and measurement of the allocation dimension. But the performance of one task can and has been empirically related to the performance of another task. The left panel of Figure 5 shows such a function between two tasks and is referred to as a Performance Operating Characteristic (POC). The corresponding resource allocation function in the

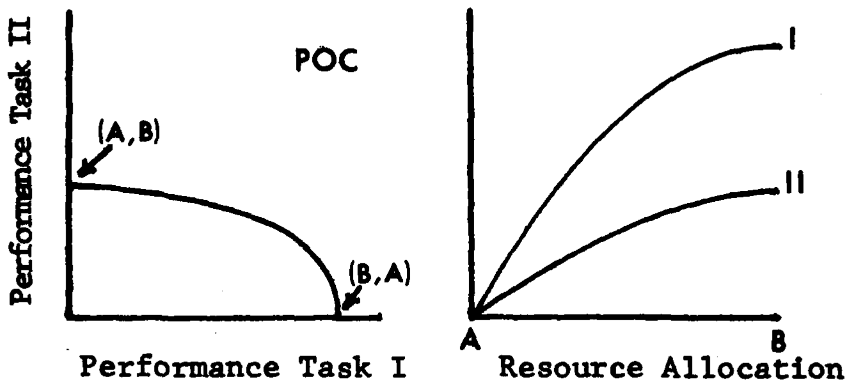

Figure 5 . Resource Allocation Functions and the Corresponding POC

right-most panel shows that the region of investigation on the abscissa is limited to the A to B region, referring back to Figure 4. As can be seen, as resources are taken from one task and applied to the other, the performance on the first task drops while the performance on the second increases. This would be a typical POC wherein both tasks are resource limited.

If the investigation were expanded to include the abscissa region shown in Figure 4 to be A to C, then the resulting POC would take a different form as shown in Figure 6. As can be seen, in the region from B to C on the abscissa, taking resources from task I to give to task II has no effect on the performance of task I. Taking from task II to give to task I, however, does effect task II's performance. Thus if the range of our investigation were restricted to the region between B and C, we might conclude

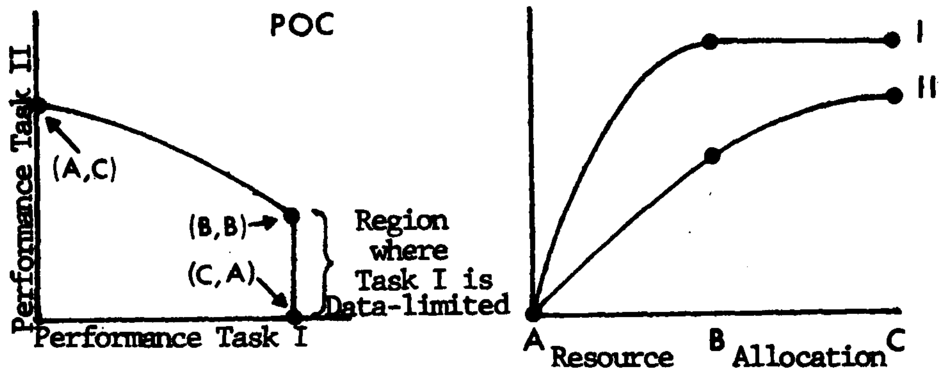

Figure 6. Resource Allocation Functions and POC

as did Kerr (1973)[17] and Posner and Boies (1971)[14] that task I interferes with task II, but the reverse is not true.

Taking this reasoning one step further, Figure 7 shows the case wherein the range of resource allocation is extended from A to D. As can be seen, one or the other of the two tasks is data-limited, displaying a rectangular POC. If the investigation were limited to the allocation

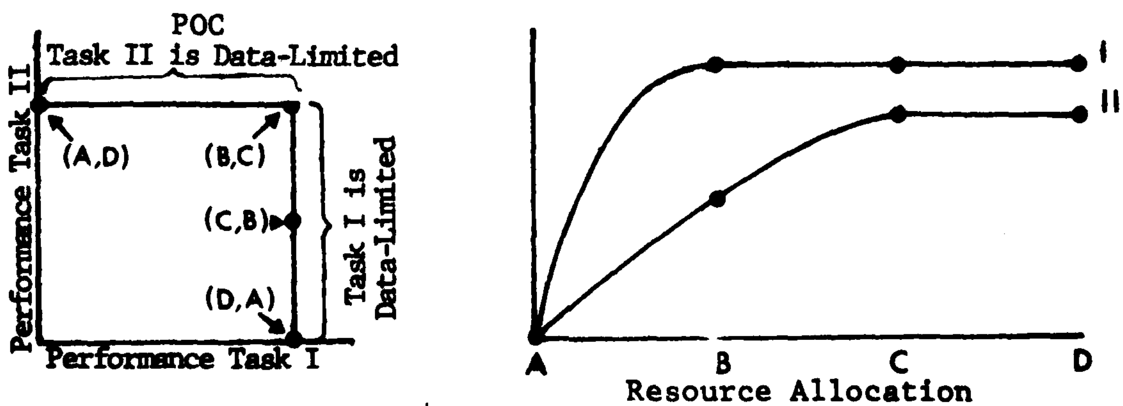

Figure 7. Resource Allocation Function and POC

ranges between C and D it can be seen from the right-hand panel that the two tasks would appear to be independent of each other. Increasing the resource allocations on task II from C to D while decreasing the allocations on task I from D to C effects the performance on neither task. Thus if the difficulty level on task II were to increase, requiring an increased effort on the controller's part in order to maintain a constant performance level, the performance on task I would not be effected, leading to the conclusion that the two tasks do not interfere with each other nor do they compete for the same central mechanism. Norman and Bobrow's (1975[21], 1976[22]) point is that tasks may have been investigated in a region wherein one or the other or both are data-limited and not resource-limited. Thus the position espoused by Kahneman (1973)[13] that there exists a very general pool of limited cognitive resources from which all tasks must draw, is quite plausible--despite the findings that some tasks appear to be independent of each other and processed in parallel.

One may ask--How then may we account for the fact that the expert controller seems quite facile with concurrent inputs and responses? The expert describes his responses as being quite automatic in nature, requiring little or no conscious processing effort. Norman and Bobrow explain that with practice, the students may learn to become more efficient in their processing, maybe by eliminating processing steps or learning only to process the minimum relevant data, etc. Thus with learning, the student approaches his data-limited asymptote more rapidly as he increases his resource allocations. This is depicted in Figure 8. With a resource function as is shown in function D, the expert performing this task would seem to be able to

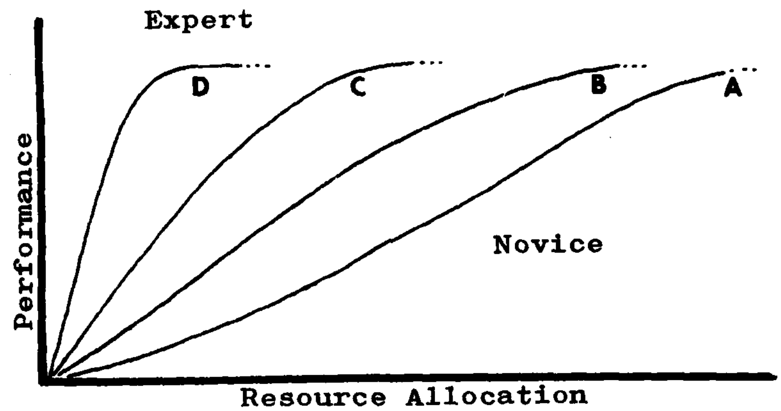

Figure 8. Changes in the Resource Allocation Functions in Various Stages of Training A Through D

do so independently of other tasks in that with very little processing effort, he achieves data-limitation status. Thus as described here, the performance on this task may not really be "automatic" but simply "cheap" in terms of the amount of resources required to reach asymptote.

An extension of Norman and Bobrow's (1975,[21] 1976[22]) theory of resource-limited processes with implications for training, comes from a group of efforts funded by the United States Air Force Office of Scientific Research (AFOSR) (see Gopher, Williges, Williges, and Damos, 1975;[23] Gopher and North, 1977;[24] Wickens and Gopher, 1977;[25] Lintern and Gopher, 1978;[26] Gopher and Navon, 1978;[27] Navon and Gopher, 1978;[28] Navon and Gopher, 1979[29]). Navon and Gopher (1979)[29] present a theory of resource allocation based on concepts from microeconomics. Without reviewing it in great detail at this point, they present several concepts which may prove helpful in establishing insights into instructional strategies.

The first is a concept which they refer to as Subject-Task Parameters which is a characterization of a subject relative to a specific task at a given point in time. These parameters would be an aggregation of indices representing predictability of the stimulus events, response complexity, amount of practice, stimulus-response compatibility, signal-to-noise ratio, etc. The set of parameters would subsume Norman and Bobrow's specifications of signal data-limits, memory data-limits and more. Performance on the specified task then is said to be a joint function of all the subject-task parameters and the momentary amount of resources allocated to the task.

A second concept of interest is the task's Demand for resources. Not to be confused with task difficulty, demand is defined as the amount of resources required (given constant subject-task parameters) to achieve a specified performance level. Task Difficulty, on the other hand, is defined as resource efficiency and given by the average slope of the performance-resource function. Assuming that the tasks represented back in Figure 4 can be compared on the same performance scale, it would follow that task II is more difficult than task I. For a fixed-unit increment in resources allocated, at a particular point on the abscissa, task I yields a greater marginal increase in performance than task II. Damand, however, would be the minimum amount of resources required (e.g. the amount represented by the distance from points A to B) to attain a predetermined level of performance (e.g. the asymptote for task I).

Finally Navon and Gopher[29] introduce the concept of an indifference curve. Indifference curves (or equal utility contours) are concepts borrowed from economics. When the composite demand of two conjoint tasks exceed the resources available, then the student must decide how to allocate the insufficient resources among the two tasks in such a way as to maximize his subjective utility relative to the joint performance. Figure 9 shows the POC of Figure 5 with a set of hypothetical indifference curves superimposed. Points a and b represent two specific points on the indifference function u_1 and on the POC. The point a represents high performance on task II relative to task I presumably because the student has invested more of his resources in task II than task I, whereas the inverse is true for point b. Because both points a and b reside on the same indifference curve however, we would say that both points represent the same level of subjective utility (satisfaction with the joint performance level) to the student, and that he is indifferent about which combination

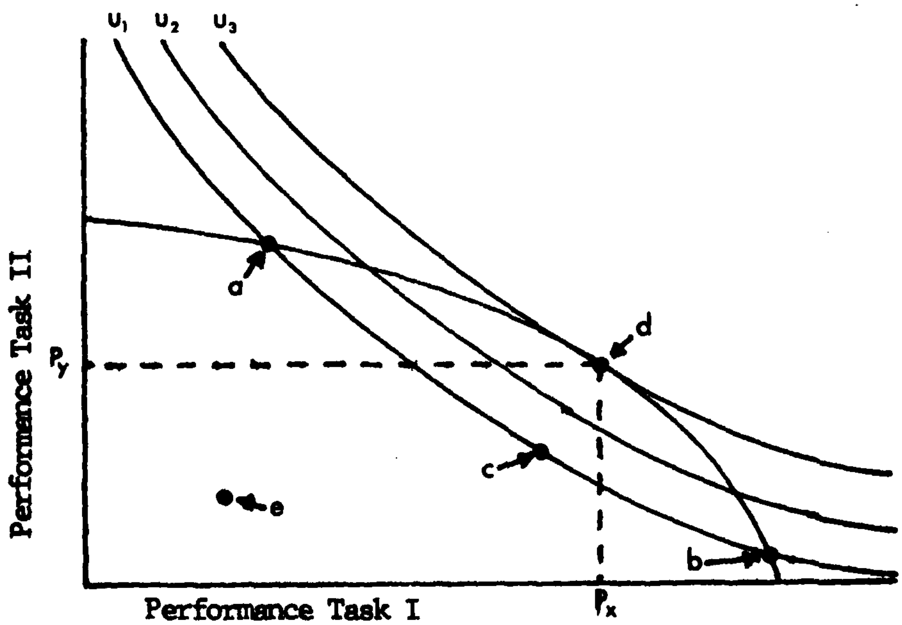

Figure 9. Indifference Curves Superimposed Over the POC

of individual task performance levels to choose. In fact, all points (including c) on u_1 represent the same utility level. All points below u_1, say point e, represent a lower utility level which the student would attempt to raise by investing additional resources. The points above u_1 represent higher utility levels which it is assumed the student would seek. However, the POC itself represents the upper limit to the combination of resource investments the student can make. Thus, it would follow that the student would select the combination of resource investments yielding the joint performance associated with the highest possible utility level. This would of course be point d on u_3. The performance levels displayed at this point in time would be P_x and P_y as shown.

The importance of the indifference curves for the development of training systems is that they can be manipulated by the instructor. Priorities on the subtask performance levels can be altered via a payoff matrix or by simple instructions. This is essentially what is being done in the dual-task studies reviewed by Kerr (1973)[17] and Hunt, et.al. (1979)[19] when one task is designated as primary on which the performance level is to remain invariant, and a second task on which performance is allowed to fluctuate. In this case, the indifference curves would represent a complete lack of trade-off as shown in the top panel of Figure 10. By increasing the difficulty level of task I, the POC is changed as is the point in which it intersects the indifference curve. But since there is a complete lack of trade-off in utility between different performance levels of the two tasks, and all u_i overlap at the minimum performance level P_x, the only adjustment the student can make is to take resources from task II to invest in task I

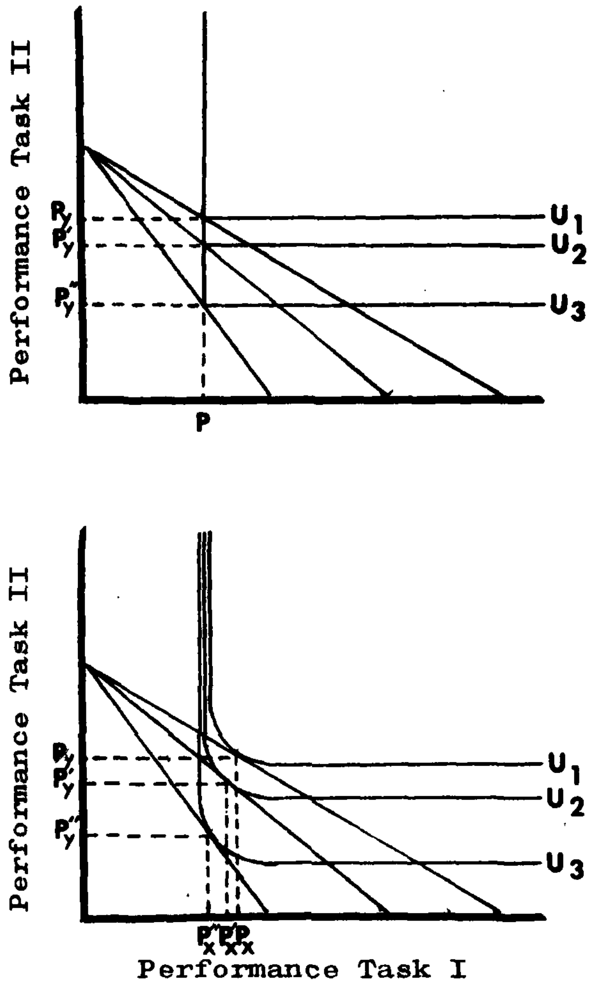

Figure 10. Indifference Curves with Indifferent Tradeoff Properties

in order to maximize instructed utility in which P_x is constant. With the drain of resources invested in the secondary as the primary task increases in difficulty, the secondary performance levels decline from P_y to p_y".

If the instructions to the student to simply consider task I as primary are not completely successful in establishing indifference curves with complete lack of trade-off properties, they might look similar to the ones shown in the lower panel in Figure 10. In this case, as the difficulty level in task I is increased, and the student seeks to redistribute his resources to attain maximum subjective utility, performance levels in both tasks are affected. It is noteworthy though, that the performance on the secondary task (P_y to P_y'') may still be more sensitive to variations in the primary task difficulty levels than the performance on the primary task itself (P_x to P_x'').

This is one possible explanation for the phenomena reported by Hunt et. al (1979)[19] wherein they commented that frequently dual-task studies are unable to hold the performance on the primary task constant. There are of course other explanations which we cannot explore here, but there is one other which is worth considering. Thus far we have assumed that the student is able to fully control his resource allocations. If this assumption were wrong (e.g. the secondary task is distracting enough that it commands a minimum amount of attentional resources), the student may not be able to shift enough of his resources to the primary task to keep P_x invariant even if those were his direct instructions and he is given explicit feedback on his primary task performance.

It is worth noting at this point that the treatment of the human processing system as the simple resource allocation theories just described, makes no mention of processing stages and makes only weak assumptions about the nature of the resources themselves. The assumptions that are required however, are given in Navon and Gopher (1979)[29] which the reader is encouraged to consult. Because of the generality of our consideration of resources and tasks, the conclusions to be drawn should prove to be quite robust with respect to a wide variety of training situations. This would, of course, be of benefit to those developing training systems, as the time constraints may be tight enough to preclude a thorough analysis of each specific task.

RESOURCE MANIPULATION IN TRAINING

Consider for a moment the situation wherein the student is confronted with a dual-task situation which he must master. We of course have not considered the case of three of more conjoint tasks because of the complexity. So consider the two tasks possibly as complex composite tasks into which simpler tasks may be mapped. As the student begins training, we might consider the source of his task priorities and his resultant indifference functions. One source would be the student's own biases, shaped by his previous experience--perhaps as a pilot. A second source would be the terminal task requirements set by the job specifications. As an example, in PAR training, the students are told that the target's position relative to elevation is more important than the azimuth. In fact, the students are given importance ratios which would indicate such. A third such source could be momentary priorities set dynamically by the training system for pedogogical purposes. Human instructors are often observed telling the students such things as, "This time concentrate more on task A than task B." This can be done in extreme when the subject is told to concentrate on one part of the display while ignoring the other. In fact, the display may be modified so that the part of the display to be ignored is blank. This extreme position, where the tasks are learned in isolation rather than conjointly, brings up the old part-whole training problem (for older reviews see Adams, 1960;[30] Fleishman, 1965;[31] and Freedle, Zavala and Fleishman, 1968[32]).

The assumption implied in making the student concentrate on one task at the expense of others is that learning rate is positively related to the amount of resources invested. In some tasks this assumption would be a foregone conclusion in that the human organism is no longer viewed as a passive learner. In information storage problems, the learner must invest resources into such activities as elaborative processing as opposed to mere maintenance rehearsal (see Craik and Lockhart, 1972[33]). This assumption would then suggest the concept of a Resource Allocation-Acquisition Function as shown in Figure 11. As can be seen, the momentary learning rate is portrayed (in this case arbitrarily) as a function of the amount of resources allocated. In this view, the rate at which a task is mastered could be altered by manipulating the resources allocated. The resources could in turn be influenced by the task priorities given the student by the instructor.

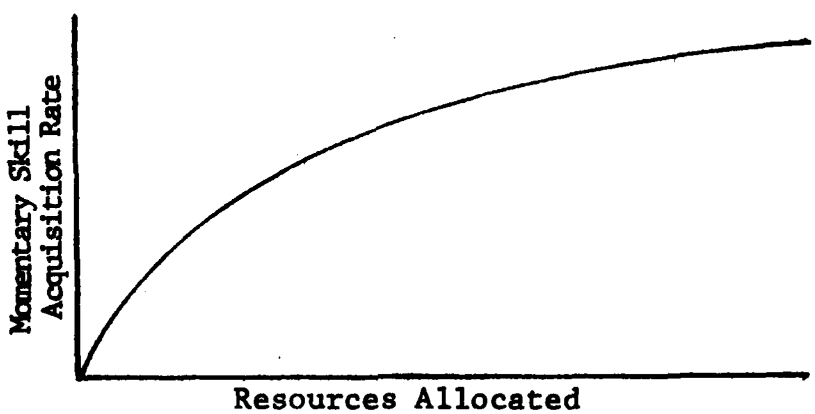

Figure 11. Exemplar Resource Allocation-Acquistion Function

There are at least three exemplar studies in which task priorities in a dual-task paradigm were manipulated (Gopher and North, 1974a;[34] Gopher and North, 1974b;[35] and Gopher and North, 1977[24]). These studies were unique relative to the rest of the dual-task literature in that they manipulated task priorities during the student's training on the tasks rather than asymptotic dual-task performance. Gopher and North (1977[24]) paired a one-dimensional tracking task with a digit-processing, reaction-time task, under the following priority conditions: (1.0,0), (.7,.3), (.5,.5), (.3,.7), (0,1.0). The (1.0,0) and (.0,1.0) comparisons were of course single-task presentations while the others were dual-task presentations. It was found that tracking performance displayed larger improvements with the larger priorities (1.0, and .7) than with the more nominal levels of (.5) and (.3). The digit processing task however was relatively insensitive to priority manipulations. In their analysis, improvements in the digit-processing task were found only in the time-sharing conditions and were attributed to an improvement in general time-sharing skills. Thus for them, the optimal priorities for training dual-task performance was (.7) for tracking and (.3) for digit processing.

Consider the hypothetical resource allocation-acquisition functions for the two tasks as plotted against each other as shown in Figure 12. As diagrammed, once the student invests some minimal level of resources in the digit-processing task, the marginal return for each additional unit of resources diminishes. Not so for the tracking task, however, which shows the momentary acquisition rate to be highly sensitive to resource investment in the region between (.5) and (.8). If the human instructor, with his training experience

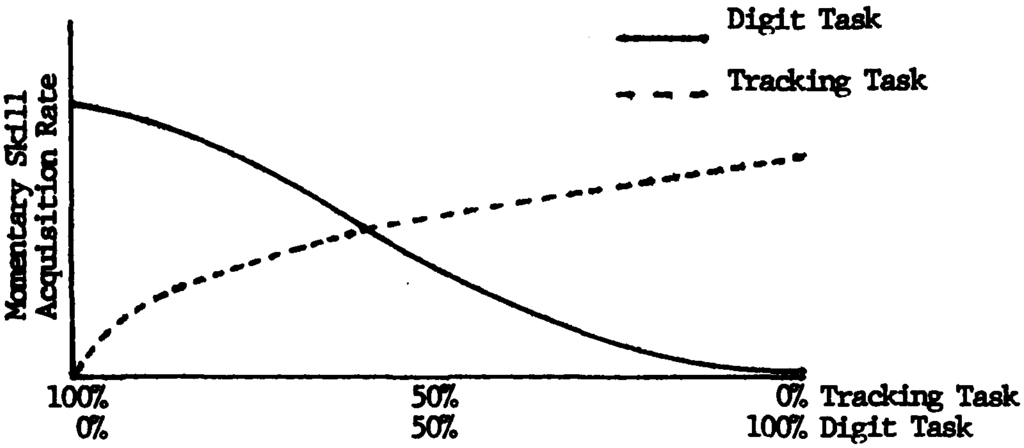

Figure 12. Resource Allocation Function.

was aware, even roughly, of these functions he would instruct the student to concentrate primarily on his tracking, while processing the digits when he can.

An intelligent automated training system could also manipulate the student's resources in real time. A set of techniques for making decisions similar to these was suggested by Chant and Atkinson (1973)[36] and is discussed by Chatfield and Gidcumb (1977).[37] Borrowing from some of the concepts espoused by Chant and Atkinson (1973),[36] suppose that the terminal priorities (post-training, in-the-field priorities) are (.5, .5). Suppose also that the control logic of the automated training system is allowed to set the priorities throughout training and that the student is given adequate feedback regarding the joint performance levels (see Gopher and North, 1977[24] about the feedback problem). Then the system could seek a division of priorities (analogous to Chant and Atkinson's turnpike solution") during training which would optimize the average acquisition rate. The term "turnpike solution" was borrowed from economics and was itself an analogy in that the most rapid trajectory from one point to the next may not be the shortest (straight-line) path. The quickest way may be to detour to the turnpike, take the turnpike at a more rapid rate, then exit the turnpike taking another path to your final destination. Thus in our dual-task case, the system's solution might be to train the student first on the tracking task in isolation in order to attain some minimum level of proficiency (the path to the turnpike), then put the student in the dual-task situation with the (.7, .3) priorities (the rapid turnpike), followed by a final short period of training with equal priorities (path from the turnpike) until the joint performance criterion is attained. This round-about solution should be quicker than simply training the student under equal priorities from the beginning.

Again it should be noted that present treatment of the human processing system is in very general terms with only weak assumptions about the specific nature of the tasks. We only assume that in the dual-task situation there is some unspecified amount of competition for processing resources between two tasks. The relationship between the two tasks may vary from one extreme, that being complete <u>task independence</u> wherein there is no extra cost for concurrence, to finally the case of <u>task incompatibility</u> wherein an extra cost for concurrence is found. We will propose in later sections that an intelligent system, using the general principles discussed, be designed to dynamically converge on an optimal solution regarding certain instructional strategies. In the present example of the Gopher and North (1977)[24] study, the system should be able to handle the training of two quite divergent tasks, one being a continuous event-driven tracking task requiring an adaptive logic (using the ratio of acceleration rate determinants of the control dynamics as an adaptive variable to keep RMS error within tolerance), with the other being a discrete self-paced digit-processing task. The intelligent system should be able to direct the student's resources even to the extent of giving one of the tasks as priority of zero by not introducing it until a later time. This control process could be extended to the decision processes of knowing when to add a third task as the marginal momentary acquisition rates of the first two tasks falls below a particular level. A more complete discussion of this control logic will be presented later. There are of course some assumptions such as: the ability of the subject to direct his resources, the acquisition of resource management skills, and the nature of the performance feedback requisite for resource management. For these reasons we deem it necessary to examine the components of the various tasks in which controllers may be required to engage, the nature of their demand for resources, and their probable costs for concurrence.

PROCESSING STAGES

Recently there has been a resurgence of interests in "stage" theoretical approaches to the information processing problem. Basically the proposition is that processing takes place in discrete and independent functional stages. Further, these stages are generally considered to be successive in nature. Thus as Sternberg (1969)[38] espoused, the reaction time (RT) of a response may be decomposed and attributed to a set of individual subprocesses. The underlying assumption is that only one component process may be active at any one time. This we will refer to as the Discrete Stage Model. It is noteworthy that a recent alternative offered by

McClelland (1979)[39] assumes that all components of a processing system operate continuously, but pass information from one process to the next as it becomes available. This he refers to as the Cascade Model.

Until now our analysis has not obligated us to break the general pool of resources into processing components. We could continue in that vein and still find it useful, in fact helpful, in deriving general instructional strategies with robust qualities relative to a wide variety of tasks. In fact we hope to show that the basic research efforts investigating the separate stages, have led to similar conclusions. The first two stages discussed are visual encoding and search and comparison. These are followed by a discussion of internal representation and its effect on the processing of the inputs and the selection of a response. Finally, response execution is discussed focusing on motor responses because of its relevance to tasks such as those required of the AIC.

ENCODING OR PERCEPTUAL STAGE. The terms "coding" and "encoding" have been used in various ways throughout the literature. In our usage, we refer to the process by which the raw stimulus data is transformed (or coded) into a form representative of an item in memory. As an example, the LSO viewing the approaching aircraft in the distance, as is shown in Figure 13, encodes the visual data in a way which matches a representation leading to further processing. The distant features may include shape of the aircraft's silhouette, the distance from the horizon, apparent movement, etc. In processing these cues, e.g. shape of the silhouette, a code is formed which matches an entity in memory. The representation in memory may indirectly, through further processing, lead to the execution of a particular verbal

Figure 13. Exemplar Silhouettes of Two Approaching Aircraft: One with a High Pitch Angle and the Other With a Low Pitch Angle

advisory on the part of the LSO. It may be that the silhouette was that of an aircraft with the pitch angle too low. Whatever the form of its corresponding code, it matches a representation in memory which eventually, with further processing, leads to the advisory "attitude."

The beginning student may not be able to perceive the subtle cues of a distal silhouette as an aircraft needing to keep his "nose up." In fact the student would be precluded from perceiving it no matter how much of his resources he invested in the perceptual process. Thus we would say the process is signal-data limited. What is required at this point is <u>Perceptual Learning</u>. LaBerge (1976)[40] describes a perceptual learning model with three stages (these are learning stages and should not be confused with processing stages). The first stage he describes as <u>Feature Discovery</u> wherein the student becomes sensitive to particular attributes of the sensory patterns. Gibson (1969)[41] referred to this process as differentiation. The ability is acquired by noting differences in a variety of sensory patterns. Two silhouettes are shown in Figure 13 which depict an approaching aircraft. Most observers using the similarities can readily identify the objects as aircraft, but only with practice can one begin to estimate the pitch angles from the silhouettes. In fact some effort is required to enumerate the differences in the patterns such as the aircraft with the greater pitch angle: having thicker wings, showing less tail, being a taller figure, etc.

If the features the LSO uses were identified then it is obvious that a part of the training task would be to point out the relevant features. The problems in identifying the features are reported by Hooks, Butler, Gullen, and Petersen (1978).[5] The verbal reports from the expert LSOs (the main source for the developers of training systems) are only partially helpful. Work needs to be carried out on methodological approaches for identifying relevant features. Some research to this end is being carried out by Gilson and Owen at the Ohio State University Aviation Psychology Laboratory (1979).[42] When the features are not known however, the old time-worn method of mere practice with feedback should work. It would be expected however that the resource allocation-acquisition function would be a non-uniform distribution, i.e. the feature discovery process on the part of the student would require resources, and that the skill's acquisition rate would depend on the resources invested by the student as directed by the system.

A second stage of LaBerge's[40] perceptual learning model is referred to as <u>coding</u>. Here a subset of the features are dealt with as a group and assigned a code. In Neisser's (1976)[43] view, this process is schema-driven, i.e. the student has developed sort of an outline or list of features for which he explores the optic array. As long as the perceptual schemata supports fine distinctions between patterns such as those in Figure 13, they are kept. If the schemata fail, however, they are modified.

A third stage assumed by LaBerge, which is of considerable interest for instructors, is that of Automatic Coding. Much of LaBerge's efforts (LaBerge, 1973;[44] LaBerge and Samuels, 1974;[45] LaBerge, 1976[40]) are invested in this concept of automaticity. In short, with extensive practice the combination of separate features are unitized or treated as a single perceptual unit. In other words, the expert LSO would automatically code the left-hand silhouette as a complete unit in some way that would represent "the nose being down" without the time and resource consuming exploration of the separate features. The importance of this unitizing process and the concept of automaticity is that it implies very fast reaction times, and little or no demands for any central resources. If no demands at all were required in automatic coding, the process would presumably be carried out in parallel with other activities. More will be said about the concept of automaticity in the next section.

At this point, it might be worth noting the role of expectations in this perceptual process. It will be recalled that the expert controller reports that with his experience he can to some extent predict the events before they occur. Thus he is thinking ahead, in an attempt to anticipate. It is hypothesized that this "anticipation or expectation" would facilitate the perceptual process. LaBerge (1973)[44] assumes a parallel hierarchical model in which the sensory input is first analyzed by feature detectors. The results of the analysis by feature detectors is then organized into codes (e.g. letters). The codes are further organized into higher level codes (e.g. words, responses, etc.) Now it is assumed that not only may the hierarchy be activated from the bottom-up via the sensory input, but may also be activated top-down via the memory system. Phrased in other terminology, if the hierarchies are viewed as schemata, we would say that the schema may be concept-driven as well as data driven (Neisser, 1976[43]).

Specifically, the advantage of anticipation is that the hierarchical network is transformed into a heightened state of excitability. The LSO would expect to see the nose drop on an aircraft which had just been given an advisory that he was above glideslope. Thus when a certain visual pattern of cues is expected, the features are coded rapidly and sent to the memory system for a match or perhaps in the case of a highly practiced hierarchy, directly to a response for execution. The power of anticipation is demonstrated by LaBerge (1973)[44] wherein the response latencies in a letter-matching task were found to be the same between novel "letter-like" symbols and familiar (and highly practiced) actual letters, when the specific letters or symbols were expected. If the letters or symbols were unexpected however, only the ordinary letters were processed rapidly as if they were automatic and unitized. It would be of interest to know for training purposes, whether the expert LSO's rapid processing of visual data is due more to automaticity or expectation. This could presumably be explored by taking RT measures on expected and unexpected events. Not surprisingly, the instructional logic would depend on the degree to which automaticity was the goal relative to expectation.

SEARCH AND COMPARISON. Sternberg (1966)[46] devised a memory search paradigm which has now become a classic. In this paradigm, as the experimenter presents a series of characters to the subject, one at a time, the subject is to check each one and indicate whether or not the character is a member of a set for which the subject was instructed to watch. The set of items, for which the subject was to check, may be referred to as the <u>memory set</u> with the elements, (the objects of the search) the <u>targets</u>. The memory set of items was usually given to the subject just before a longer series of items (termed the input items) was presented. The list of input items contained items which were not in the memory set, and were termed the <u>distractor set</u> with elements being called <u>distractors</u>. With this paradigm, Sternberg[46] found that the RT to each input item was a function of the number of items in the memory set. As an example, a set of input items which might be presented to the subject one at a time would be: <u>a</u> f k <u>b</u> a g <u>h</u> z g <u>a</u> <u>b</u> w. . . The set of items for which he is searching (the memory set) is (a, b, h) and each of the members is called a target. In the list of input items we have underlined the targets. The rest of the letters would be the distractors.

The theory emanating from these findings was that the subject performed a memory search with each input item, i.e. when an item was presented, the subject would compare it in a serial fashion with each member of the memory set. Over the years, there arose some controversy (which we won't review here) as to whether the subject terminated the search as soon as he found a match, or whether he continued the comparison process until the memory set was exhausted. Of interest in the present context was that the reaction time required for the subject to perform this memory search and comparison task was about 40 msec per item in the visual display, plus a constant.

More recently Schneider and Shiffrin (1977)[47] presented a hybrid search task which included components of both visual and memory search. Essentially this consisted of presenting the input items in sets of 1, 2, or 4 rather than single items in succession. Additionally subjects were given a memory set size of 1, 2, or 4 items. Thus at the extremes, a subject may be given a single input item to be compared with a single memory set item, or simultaneous presentation of four input items with four items in the memory set constituting a total of 16 comparisons (assuming the search is exhaustive). If the comparisons were made in a serial fashion, then RT would be expected to be a joint function of the memory set size, and the display set size as shown in Figure 14. Corrected for the intercept, RT would be 40 msec per comparison. This is essentially what Schneider and

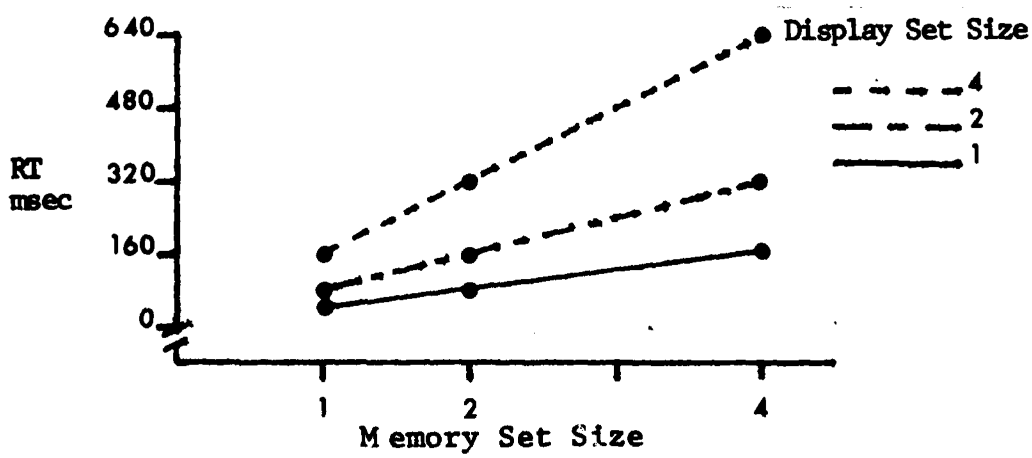

Figure 14. Reaction Time as a Function of the Memory Set and the Display Set

Shiffrin[47] had found, although their actual data was in a more complex form. Similar findings were reported by Briggs and Johnsen (1973).[48]

Of additional interest is the use of accuracy as opposed to RT. One would surmise that if the serial search and comparison is a process which consumes time, that accelerating the pace with which the display sets are presented would interrupt the process and depress accuracy. Further, the presentation rate would interact with memory and display set sizes. This was essentially the findings Schneider and Shiffrin reported in experiment 1.

Both Griggs and Johnsen (1973)[48] and Schneider and Shiffrin (1977)[47] report that under certain conditions, extensive practice reduces the slope of the RT-comparison functions to almost zero, i.e. the RT required for search and comparison was nearly a constant for varying sizes of the memory set and display set. One of the requirements for this phenomenon was, of course, the extensive practice, while the second was that the subject be trained under what Schneider and Shiffrin[47] termed <u>consistent mapping</u> (CM) conditions as opposed to <u>varied mapping</u> (VM) conditions. The CM training conditions are those in which the type of items (e.g. numbers) that are designated as targets, never become distractors while the type of items designated as distractors (e.g. letters) are not used as targets. Under VM training conditions, items used as targets on some trials may be distractors on other trials. Schneider and Shiffrin contend that under CM conditions the processes become ones of <u>automatic detection</u> and <u>automatic search</u>. Under VM conditions, the slower, serial, set-size dependent processing that obtains is referred to as <u>controlled search</u>.

As LaBerge (1976),[40] Schneider and Shiffrin (1977)[47] devote much of their effort to establishing a qualitative as well as a quantitative difference between controlled and automatic processing. The first difference has already been noted, that automatic search is not affected by load. Accuracy and RT under CM training conditions are relatively constant when the size of either the memory sets or distractor sets are increased. Thus automatic search becomes an emerging goal of instruction as the automaticity would be a valuable asset in time-sharing tasks in that it would require minimum resources. A second difference is that in controlled processing, if a second target follows the first in close temporal proximity, the second target is frequently not detected, presumably because the first is still being processed. But in automatic processing only the simultaneous presentation of two targets produced a slight decrement. Further, the two targets being identical facilitated the performance of controlled processing while degrading automatic detection, a finding which the authors contend shows support for the notion that automaticity is qualitatively different than controlled processing. A third difference is reported by Shiffrin and Schneider (1977)[47] regarding the rigidity of the automatic processing. They report that the reversal of the target/distractor status of the items has minimal effect on post-reversal learning under controlled processing. However, if the original target/distraction distinctions were trained extensively under CM conditions, then subsequent reversal training is extremely difficult: the idea being that once the automatic detection processes are developed, they are difficult to modify or reverse.

A fourth difference between automatic and controlled processes, comes from focused attention experiments. In these paradigms, subjects are presented with some form of a divided display. They are to focus their attention (allocate all their resources) on one part of the display while ignoring the others. Both targets and distractors may be displayed in the to-be-attended portion of the display. All inputs in the to-be-ignored portion of the display are referred to as foils. Typically performance on the attended portion of the displays are effected by the foils. When the foils cause a drop in performance, this is referred to as a focused attention deficit. Within the present context, focused attention deficits imply resource allocation rigidity. It was shown by Shiffrin and Schneider[47] that foils which were targets established under CM conditions caused pronounced focused attention deficits whereas VM trained foils did not. It was argued that once an automatic detection mechanism is established, any input (in any portion of the display) which triggers the mechanism will cause it to run its full course. The mechanism's status as automatic, implies that it is not under the conscious control of the subject. The VM target foils, though they may be encoded, seem to be suppressed in terms of any further processing and are not a burden on the focused attention performance. Anecdotal reports by the subjects in these experiments further demonstrate the automaticity quality of these CM trained targets. Subjects report that the targets being certain letters, seem to jump out at them even when doing normal reading.

In the visual and memory search studies described thus far, the subjects were not able to anticipate the nature of an item before its presentation. In the controllers tasks, we reported that anticipation was possible and probable. The continuous flow of connected information on the display would be highly predictable with experience. Thus the role of expectation is important. It will be recalled that LaBerge (1973)[44] reported that RTs to novel stimuli were comparable to familiar stimuli when cued. Klatzky and Smith (1972)[49] also showed shorter RTs for cued items that would have been trained in VM conditions, LaBerge felt that the role of expectancy would impact the process in the encoding stage by placing the encoding hierarchy for a particular event in an excitatory state. Sternberg (1975)[50] felt that it was the comparison process which would be speeded for an expected item. Shiffrin and Schneider (1974)[51] also note that the major role of the expectancy could be in the response production stage. At this point, whether expectancy affects the encoding stage, serial comparison, decision making, the response production stage or possibly all stages, is not clear.

Just how much of a role automaticity and expectation might play in a controller's search task is not readily apparent either. Introspective reports on the GCA-CTS indicate that there are certain "things" that a novice keeps "looking for" in the display during an approach. The novice reports that in a sense he cycles through a "check-list" of cues for which he scans the display (elevation intersect, elevation trail, range hashmark, azimuth intersect, etc.). This check-list, however it might be verbalized or formulated, acts similar to the memory set in memory search studies. Further, the display itself presents the novice with a continuous flow of multiple inputs requisite for the visual search portion of the task. While the novice is cognizant of some kind of a search process, the expert is not.

Does this mean the expert engages in some kind of automated search, or do his expectations lead him to a cyclic rhythm of controlled processing (or both)?

The 12-14 hours of PAR training the students receive could constitute enough trials (under CM conditions) for some automatic processing to begin to occur. It was estimated that during their training time, they would have made approximately: 42-54 calls per approach, 5-8 approaches per session, and 12-16 sessions in total, constituting roughly 2,500 to 7,700 calls made during training. Shiffrin and Schneider (1977)[52] in experiment 1 report automaticity within roughly the first 2,100 trials of CM training, with 600 trials per day. However, the memory set was well defined (simply a set of characters) as was the display set. The novice controller reports "checking for things" but the exact internalized form of the "things" is not apparent nor is it obvious that this subjectively contrived memory set to which the novice is referring, is consistent across trials, a condition necessary for the consistent mapping requisite for automaticity. In fact, the student is probably reorganizing his internal structure at various junctures in his training. Thus the PAR instructor may be right when he feels that his students are not operating with automaticity following only 12-16 hours actually on the display, whereas the expert's performance after 1-2 years as controller may be. There would be several possible ways of testing the automaticity of the 12-16 hour novice, and the expert if developed. Some analogue to the Stroop Color-Word Interference Test (1935)[53] could be contrived in which the expert and novice could be compared on a task requiring them to make incompatible verbal responses to the events displayed on the scope.

In this case, automaticity, to the extent present, would work against the expert, possibly degrading his performance more severely than the controlled processing novice (see Keele, 1972;[54] Eriksen and Eriksen, 1974[55] for examples).

PROCESS VS. STRUCTURE. At this point we would like to make a distinction between process and structure, although the state-of-the-art is such that a rigid delineation between the two concepts is not always possible. We will take <u>structure</u> to refer to the internal organization of units of a knowledge domain. As an example, in the memory search tasks of Sternberg's, the list of items in memory through which the subject must search, constitutes a simple structure. The search activity itself would be an example of what we will refer to as <u>process</u>. It is obvious that errors may be caused by deficiencies in either process or structure. If the search process itself is interrupted prematurely by perhaps incoming distractors, a match may go undetected. If one of the members of the memory set were inadvertantly lost, again a match may go undetected. The point is that both process and structure could lead to the same error-- a missed target.

It would be important for an intelligent training system to be able to diagnose the causes of all the various types of errors that a student could make so that each could be rectified in the most expeditious manner. However at this point, we will be content with a simple binary diagnosis of the errors being either process or structurally precipitated. One way the system could diagnose the "missed-target" errors in the present example would be to vary resource allocations. Process deficiency precipitated errors sould be a function of resource allocations and would thereby be termed errors of resource-limitations.

Errors due to structural deficiencies however, would appear to be data-limited in that large increases in resource investments would not reduce the amount of information or potential distractors in other parts of a complex display so that the student could "concentrate" on his memory search process. Such increases in concentration on the search process should increase performance providing the problem is not structural. If it is, say an item is missing from the memory set, then no amount of increase in concentration (resources) will improve performance.

The importance of the process-structure distinction lies in differential instructional strategies. In a gross sense, increased efficiency in processing comes with practice, while structure is modified and built through instruction and the imparting of knowledge. In our memory search example, if the system had determined that the misses were due to resource-limitations, it would prescribe additional practice on that part of the process until it becomes more automatic and requires less resources. If however, the system had determined that the misses were due to data-limitations, it could stop and query the student on structure (memory set). When it found that part of the memory set was missing, it would proceed to rectify the situation through tutorials as to the proper memory set and then return to the main portion of the training system.

Our distinction between process and structure is not as clear as we would like however, Empirical evidence (Briggs and Johnsen, 1973;[48] and Schneider and Shiffrin, 1977[47]) shows us that processing becomes more efficient (requires less resources) even to the point of automaticity, possibly, with extensive practice. It is not apparent, however, as to what exactly has changed in the processing that makes it faster and more automatic. This is especially so in a more complex situation such as a controller. Here there is more than a simple memory set to be examined wherein a "match" leads to a simple "detection" response. The unspecified units to be searched, rather than being in a list form may be related in various ways forming a complex network. Further, once a "match" is found, additional processing may be required in order to construct the correct form of the response. With extensive practice can we say that the search through the complex network, and the construction of a response becomes automatic, so that it may be carried out in parallel, (i.e. the same number of steps are required but are now processed without effort)? Or may we say that with extensive practice certain steps may be eliminated, or the organizational structure is somehow modified and streamlined, so that the input data leads more directly to the response? To this end we need to look at structure, the problem of how knowledge is internally represented, and the process by which detection of some event ultimately leads to the selection of a response.

There has been much research effort of late which has been directed toward this problem of internal representation and structure, a good portion of which has been funded by ONR. Several models of interest have been proposed by Anderson (1978),[56] Collins and Loftus (1975),[57] Hayes-Roth (1977),[58] Kintsch (1972),[59] and Norman, Rumelhart, and the LNR research group (1975).[60] The terminology differs somewhat but most of the models are derivatives of what was termed Associative Network Models.

Most current models assume that knowledge exists in memory in conceptual chunks. These chunks, on cognitive structural units have been described variously as records (Norman and Bobrow, 1979[61]) schemata (Anderson, 1978;[56] Bobrow and Norman, 1975[62]) cogits (Hayes-Roth, 1977[58]), frames (Minksy, 1975[63]), and nodes (numerous authors). In their usage, these terms are in no way synonyms, but all refer in an abstract way to separate knowledge entities. In attempting a short amalgamation of the concepts of the various authors, the terminology presented by Norman, Bobrow, and their colleagues is relied upon heavily, due to the continuity of their efforts from about 1975. Some variations in the usage of terms arise however, when attempting to incorporate principles from other authors. Readers interested in more detail in these areas are encouraged to examine the original sources.

The "vague" chunks of memory will be referred to as schemata, a term used in various ways by several authors. By this we will mean a segment of knowledge organized around a central concept or theme. An example of a schema in its simplest form would be the frame-like notation presented by Minsky (1975)[63] for representing knowledge in the computer. Here a "frame" is a description of an object, or action, which incorporates all the invariant features common to instances which would be classed as an example of the particular abject or action. Kuipers (1975),[64] discusses and lists the properties of frames, while Bobrow and Norman (1975)[62] and Winograd (1975)[65] discuss some of the underlying issues leading to more recent modifications of Minsky"s ideas.

An example of a frame-like schema is given by Bott (1979)[66] and is shown in Figure 15. The schema is similar in a way to the older idea of concepts (see Trabasso and Bower, 1968 [67]) in that the schema is seen as a knowledge

DOG
- Head
- Body
- Tail
- Color
- Location
- Breed
- Age
- Name
    - to find name: examine dog collar (procedure)
- Owner
    - to find owner: examine dog collar (procedure)

Figure 15. Exemplar Schema for the Concept Dog

unit comprised of slots for the attributes or features by which it is defined. The schema is more than this however, in that the slots may contain subparts, supersets, and important in the present context, procedural information.

Bobrow and Norman (1975)[62] make the assertion that schemata are comprised of context-dependent descriptions. They proposed that the descriptions were formed by selecting a set of descriptors which would unambiguously set apart the object or event in question from other referents present in the current context at the time of the description's first usage. If a child first forms an internal representation of a "dog" in the context of a farm with much larger animals, then his set of descriptors would differ somewhat from the formation of a description in a different context. New experiences, such as subsequent encounters with "dog-like" organisms are interpreted and classed by the original context-dependent descriptions. Thus the original encounters serve as prototypes for subsequent encounters (Norman and Bobrow, 1979[61]).

The function of schemata is not only to aid the person in functioning in an environment in which he is already experienced, but also in novel situations. In a new situation wherein the input does not match existing schemata, a search is made for a "near" fit in an analogical or metaphorical sense by selecting perhaps a schema from a different context. Norman, Gentner and Stevens (1976)[68] present an example of this in their Mayonnaise Problem. Subjects were asked their opinion regarding the probable ingredients of mayonnaise. Being a white creamy substance, the naive subjects often responded with dairy products, the result of existing schemata. Nowhere in their existing schemata could the results of the interaction between egg yolks and oil producing a white creamy substance, be found. Thus, confronted with this new problem, the subjects selected a schema by analogy and then proceeded to modify the structure until a solution could be output.

Of present interest regarding the training of radar controllers, is the relation between schemata and resource consuming events. Assume for the moment that schemata may be both event-driven, being a "bottom-up" (Bobrow and Norman, 1975[62]) process, or conceptually-driven as a "top-down" process (Goodman, 1976[69]). In an event-driven situation as described in the previous section, an input generates a description which must be compared with potential schemata. Early in training this search and comparison process (if that is all it is) consumes both time and resources. If a quick match is found, the input is fit into a context which may provide a further input to a higher level schema, or may lead directly to procedural information for response production. If a match is not found however, the central resources are then required to examine the degree of mismatch in the various comparisons. The mayonnaise problem would be an extreme mismatch problem in that considerable resources and time would be required to generate a response. Even with no other concurrent tasks and unlimited time, the students could not give the correct ingredients, which would make the problem a data-limited (or memory-limited) task caused by structural deficiencies. Note that mismatches do not preclude responses from occuring. If however, the degree of mismatch is slight, the central *mechanism*, having access to a wide array of schemata, may be able to resolve the mismatch leading eventually to the appropriate response. Unavailability of the central mechanism or severe time constraints would prohibit responding or cause the central mechanism to execute some default option in its output which would very likely be an error.

One cause for resource and time consumption then would be the occurence of mismatches, which speaks of the importance of the development of adequate descriptions and prototypes during training. A second possible relationship between resource and time consumption and structure could be in the strength of the structure. Hayes-Roth (1977)[58] proposing a slightly different network model, posits that a knowledge structure changes in strength as well as, possibly configurations. In her treatise, the smallest cognitive units of information are called <u>cogits</u>. The cogits, activated in an all-or-none fashion, are assembled via associations into larger configurations. A particular configuration is said to have "strength" as a function of the strengths of the separate associations between cogits. With extensive practice the assembly can eventually be strengthened to the point of "unitization" whereupon it may be activated on in a discrete all-or-none fashion. Hayes-Roth and Hayes-Roth (1975),[70] and Perlmutter, Sorce, and Myers (1976)[71] both report reaction times in verifying a learned proposition decreases with practice. Thus for training applications, mere practice and repetition may not only effect process but also the strength of a structure. However, here the distinction between process and structure blurrs somewhat in that the strength is inferred by activation speed which would be process.

Expectation can be thought of as the activation of a schema, or series of structures in a top-down sense, just prior to the next input. As an example, suppose that an LSO, tracking an approaching aircraft just above the horizon, notices a puff of smoke from the tail. This additional exhaust emission would result from the pilot applying more power. The visual input in that context would activate the appropriate schema corresponding to the increase in power. In addition to any procedural component activated in the schema, the schema could provide conceptual input into another schema corresponding to gains in altitude. Thus the first schema was data-driven while the second was conceptually driven. Having just detected a puff of smoke, he now "expects" to see a gain in altitude. The reader may want to refer to Anderson (1978)[56] regarding a discussion of data-driven and conceptually-driven processes in the act of reading.

Rumelhart and Norman (1976)[72] and Norman (1978)[73] propose that the learning or formation of the cognitive structures occur in three overlapping stages. The first stage which they called accretion of knowledge, most generally refers to the accumulation of new information and facts in accordance with existing knowledge. During this stage, the instructional system is adding to the underlying data base of the learner. Incoming information is organized via existing knowledge structure. Thus a student with prior experience in a different type of air traffic control would find additional control duties easy to acquire because he had extensive structures in this area already formulated. A complete novice however, may be forced to generate structure from scratch as it were. As an example, the novice, having had no previous schemata established regarding radar technology, must use his existing knowledge to understand how it works. Choosing a prototype from another context, he may decide that radar must be something like photography. So he begins to establish his conceptualization of radar around what he knows of photography. As one might guess, the student will encounter various situations where this analogy will break down.

The second stage is referred to as restructuring. When the existing schemata cannot handle the new knowledge, the schemata themselves may need to be reorganized. It is the restructuring of knowledge, rather than the addition of new facts, which leads to the kind of phenomena we call "insight." The novice may have television and radio transmissions, visual sensations, auditory sensations, radar return, and photography all compartmentalized as entirely different entities. But if questioned about the similarities in the type of signals transmitted and received, the student may come to conceptualize light, sound, radio transmissions, radar return, and even heat as basically the same thing, differing only in wave-length or frequency. The type of training to produce this phenomena, would probably be that of a "Socratic tutor" (see Stevens and Collins, 1977[74]) which would pick at the student's present knowledge structures exposing the inadequacies of his present schemata, so that they might be modified. The restructuring stage we would associate most with the concept of understanding.

Of special interest in the training of controllers is the third stage referred to as tuning. Once the new knowledge has been added to the data-base, perhaps causing some restructuring of the existing schemata, the schemata undergo additional minor changes depicted as "fine tuning." Here the processing associated with schemata undergoing tuning becomes streamlined, more efficient, requires less resources and eventually reaches a stage of automation. Rummelhart and Norman (1976)[72] suggest that in tuning, the structure remains unchanged with only the constant and variable terms to which they refer undergoing revision. These terms can be changed by: improving their accuracy, extending the range of the variables to generalize the applicability, constraining the variables to make the applicability more specialized, and the assumption of default values for certain variables when the variables go unspecified. This last modification, the assumption of default values, may be an important feature of a finely tuned schemata during the processing of a highly speeded task.

Norman (1978)[73] views these three modes of learning as occurring essentially in the sequence of accretion first, then restructuring, and finally tuning although the sequence is not one of discrete stages. All modes are probably present throughout training but differ in the degree to which they are occurring. In general, the instructional prescriptions for the three modes of learning respectively would be:

(1) presentation of information and facts in lecture, textual material, etc.

(2) the posing of problems and questions designed to expose structural deficiencies, and finally

(3) extensive practice for the necessary tuning.

RESPONSE EXECUTION. There are currently two major theories that dominate and generate research in the area of the learning and retention of motor skill. These are Adams' (1971)[75] closed-loop theory, and Schmidt's (1975)[76] schema theory of motor behavior. The two are fairly consistent when considering the effects and importance of certain variables and dimensions, but they do differ in important ways. Each theory reflects the current zeitgeist to develop analytical systems in terms of information processing considerations. Being the earlier account, Adams' (1971)[75] approach retains vestigial nomenclature from the period of S-R domination of accounts of human behavior. Schmidt's (1975)[76] theory relies less heavily on S-R conceptualization, but none-the-less, may be easily related to Adams'.

Adams' theory contains all the requisites for it to be classified as being closed-loop. Specified by the theory is the development of a reference mechanism for movement. The reference mechanism is defined by the occurences of response-produced stimuli during the learning of the criterion response, and comes to be an internal standard for correctness. Subsequent feedback from a response is compared with the reference and discrepancies are recognized as errors to be corrected. The theory is centrally concerned with the feedback mechanisms that are involved in the learning and retention processes.

The reference mechanism developed during acquisition is called the <u>perceptual trace</u> and it is a function of all the stimuli associated with the response. Any sensory modality acting at the time of acquisition contributes response-produced stimuli that are a part of the resulting perceptual trace. The strength of the perceptual trace is a positive function of the number of times the stimuli from which it is developed are experienced.

The perceptual trace can be viewed as a version of the image or representation in perception. A position mentioned previously in visual perception is that one recognizes objects when their stimuli arouse and match a perceptual internal representation acquired from prior experience. In a like manner, a subject can recognize a response that he has made before when feedback stimuli arouse and match the perceptual trace of that response. Knowing the correctness of a response is a matter of response recognition governed by the comparison between current response produced stimuli and the perceptual trace. If an insufficient match is made and an error is detected, the response-generating mechanism can deliver a new response which in turn is subjected to the comparison process. This continues until a successful match occurs or until the system is exhausted of potential responses.

The response-generating mechanism is called the <u>memory trace</u> and it governs the selection of responses to be subjected to the comparison process. The memory trace is seen as the associative agent responsible for the activation of a response. The memory trace is important because it is the process which activates the response in the first place with the perceptual trace governing the extent of the movement. It is necessary to postulate the existence of this second memory component because there must be independent agents governing the elicitation and comparison processes. If one agent were responsible for both, the response would necessarily be checked against itself and no errors would be detected. The memory trace may be viewed as a modest motor program which only governs the choice of responses, not extent or duration as other conceptions of a motor program might have it. Moreover, there is a sufficient body of evidence suggesting that verbal recall and recognition reflect different memory processes wherein recall is seen as response production and recognition as response identification (although these may not always be mutually exclusive; Marshall and Smith, 1977[77]). Parsimony would require the same division of motor memory. The two mechanisms of perceptual and memory trace are seen as the basis for recognition and recall, respectively.

According to Adams' theory, forgetting can be accounted for by a deterioration both of memory and perceptual traces. A response produced by a memory trace weakened by forgetting will induce the selection of inappropriate movements. Deterioration of the perceptual trace will result in a poor reference mechanism and, even if the memory trace initiates a correct response, the reference mechanism may be so deteriorated as to make a match impossible. The theory as presently stated says nothing about the mechanisms of forgetting, only about the results of the operations of these mechanisms. Major mechanisms that have been postulated are trace decay and interference. The learning and retention of a movement always occur in the presence of time (trace decay), and the interaction with other movements and their perceptual traces (interference). Whether the memory trace and perceptual traces undergo a spontaneous decay, are effected by interfering stimuli, or both, is an issue not decided by the theory. However, a comprehensive theory of learning in general, and motor learning in particular, must incorporate some mechanisms for forgetting.

In one study, Adams, Goetz, and Marshall (1972)[78] were concerned about the role of response-produced feedback during acquisition trials when knowledge of results (KR) is delivered after each response and on trials where KR is withdrawn. The data supported the theory in several ways:

(1) Performance in acquisition was positively related to amount of proprioceptive feedback;
(2) Performance on KR withdrawal was better with augmented than with impoverished feedback;
(3) Performance was positively related to amount of practice and strength of the perceptual trace;
(4) Performance during KR withdrawal was determined by similarity of feedback during acquisition and KR withdrawal.

Marshall (1972)[79] in a study comparing recognition and recall in short-term memory, concluded that "Though the two measures required different behavior on the part of the subject, the closed-loop theory would view them both as being determined by the state of the perceptual trace at the time of test, and they both should be the same function of the same variable" (page 152). The results supported the theoretical assumption.

The Marshall (1972)[79] study was the first to subject the notion of recognition in motor memory to empirical test. Adams and Goetz (1973)[80] made use of a similar methodology to empirically separate the error-detection from the error-correction processes. The essence of their methodology was that ability to recognize a test movement as being different from the previously experienced criterion movement would reveal the error detection capability, while in a second study, an attempt to correct an erroneous movement would reflect the degree of error correction ability. In their study, both the effects of feedback and KR trials were potent variables, as closed-loop theory suggests.

While there are sufficient data to substantiate the existence of error detection and correction processes as postulated by Adams, there remains the issue of the nature of the reference mechanism itself, how it develops, and how it operates. Chief among the critics of Adams' (1971)[75] theory has been Schmidt (1975),[76] who published a seminal article on "A Schema Theory of Discrete Motor Skill Learning." The essence of Schmidt's theory is based "on the notion of the schema and uses a recall memory to produce movement and a recognition memory to evaluate response correctness" (page 225). At first reading there appears to be little discrepancy with Adams, but one important difference that has generated much recent research concerns the nature of the reference mechanism. Instead of the development of an internal perceptual representation, Schmidt states what actually develops is a schema for the response similar to the schemata reported earlier. A schema is defined as "a characteristic of some population of objects, and consists of a set of <u>rules</u> serving as instructions for producing a population prototype (the concept)" (Evans, 1967 page 87[81]). According to Schmidt (as well as Posner and Keele, 1968;[82] Bartlett, 1932;[83] Evans, 1967;[81] Neumann, 1974;[84] 1977[85]) as exemplary stimuli are experienced the subject develops a prototype of them and, depending on the paradigm, is capable of recalling or recognizing the prototype without ever having experienced it. Schmidt's schema results from the integration of information stored about:

(1) the initial conditions,
(2) the response specifications for the motor program,
(3) the sensory consequences of the response produced,
(4) the outcome of that movement.

It is further assumed by the theory that variable input of movement may provide an even better basis for the later recall of the prototype movement than would constant practice to the criterion movement.

This and other points of controversy between the two theories have been the focus of, and have some support in much recent motor memory research (Kelso and Norman, 1978;[86] McCracken and Stelmach, 1977;[87] Newell, 1973,[88] 1974,[89] 1976b;[90] Newell and Chew, 1974;[91] Newell and Shapiro, 1976;[92] Schmidt, Christenson and Rogers, 1975;[93] Williams, 1978;[94] Williams and Rodney, 1978;[95] Zeloznik, 1977;[96] Zeloznik and Spring, 1976;[97] Zeloznik, Shapiro and Newell, 1978[98]).

The issue at hand in this report concerns the acquisition of a complex motor skill such as is represented in the AIC task via an automated instructor model. The theoretical counts just presented place major emphasis for accurate performance on the individual's ability to monitor his performance of errors and to correct those errors when they occur. One of the most, if not the most, important determiner of that ability during learning is the nature of the feedback that the individual receives during training. Knowledge of results (only loosely analagous to the

Skinnerian concept of reinforcement) is taken as the training vehicle for the acquisition of this ability. In a recent review of currently accepted thinking about knowledge of results (KR) Adams (1978)[99] reviews four "legacies" of Thorndike (1913,[100] 1932,[101] and 1935[102]) that are today tacitly accepted and explores some of their ramifications for motor learning. These will be reviewed briefly here since they offer some ramifications for extended research on skill acquisition.

The first of these is the observation that punishment is hardly ever used in the shaping of motor behavior. Adams' search for literature concerning the use of physically aversive KR was "almost in vain." The only exception has been the series of experiments conducted by Payne and his associates (Payne, 1970;[103] Payne and Artley, 1972;[104] Payne and Richardson, 1972,[105] 1974;[106] and Payne and Dunman, 1974[107]). In these studies, Payne has shown that a previously neutral stimulus, having been associated with an aversive electric shock, can be an effective signal for off-target behavior in a tracking task. The assumed mechanism is the fear generated by that stimulus when the subject wanders off the target on the tracking task. There is also the alternative hypothesis, however, that the emotional component merely makes the signal a more distinctive cue.

The second consideration concerns the time at which, and the number of times, KR is delivered. In the typical learning situation, KR is delivered at the end of the response, and if this response is complex, the entire sequence must occur before feedback is given. In essence, the achieving of the goal is the event that initiates KR, but the steps that provide the means for achieving that goal are typically occuring without the potential benefit of KR. As Adams (1978)[99] states, "The price that we have paid for following this tradition is that we know little about training precise movement sequences in reaching a precise endpoint. . . It is time we begin thinking about scenarios of multiple KR events that will train long movement sequences in attaining goals" (page 233).

The third Thorndikian legacy is that KR is assumed to be the agent responsible for the strengthening of "habits," "bonds," or "connections." In possible refutation of this S-R conceptualization, Adams considers that the motor learning situation may be characterized as one in which the individual is chiefly concerned with detecting and reducing error. Unlike reinforcement, KR is delivered in the hope that the individual changes the next response so as to make it more reflect the standard. Thus for Adams, KR has a definate motivational component designed to bring the individual into a more error-free state.

The final point concerns the nature of KR. Knowledge of results has been assumed to be an objective, external event, yet Adams and others have challenged this since we have the ability to judge the correctness of our own responses (Adams and Bray, 1970;[108] Adams and Goetz, 1973;[80] Newell, 1974[89]). He argues for the notion of "subjective reinforcement" and for the "fascinating implication. . . that after some learning with KR has occurred, and the power to appraise our own error subjectively is developed, we should be able to learn without KR because the error information for response correction is now available from within us," (page 237).

Human Performance Model. Adams (1971),[75] Gentile (1972),[109] and most recently Marteniuk (1976)[110] have all made the observation that the study of skilled behavior has historically been piecemeal in nature with little in the way of theory to act as a unifying thread for the research. Adams (1971)[75] has even gone so far as to "blame" applied research for this dilemma since the emphasis there is usually on solving a particular problem at a particular time.

Marteniuk has recognized this absence of unifying thinking and in his recent text on the matter (1976)[110] he has attempted to produce "a unified concept of how man performs and learns skills." In his presentation, he documents not only the underlying theoretical concepts involved in skill learning, but also a practical model for the teaching of motor skills. This section will review the essential elements of the human performance model (HPM) described by Marteniuk as well as the implications they have for the teaching of skills.

The model is essentially an information processing model pertaining to motor skills that has as its major components: (1) attention mechanisms, (2) perceptual mechanisms, (3) decision mechanisms, and (4) effector mechanisms. The incorporation of each of these components into the general HPM is based upon the "state-of-the-art" in each area. A reader with general knowledge of these areas should be able to follow the integration of them and no attempt will be made here to assess individually the validity of the assumptions about them. The reader should be cautioned however, in that some of the conceptual conclusions are still in a state of evolution. For an example, the model assumes in the discussion of memory factors, a multiple storage representation of human memory. This has been substantially criticized by Craik and his associates (see Craik and Lockhart, 1972[33]) in their development of a "levels of processing" framework for memory research (itself the target of more recent criticisms!). It is the case, however, that the final vote on this matter is still to be taken, and at any rate, for much of the motor theorizing to date the multiple stage approach still enjoys considerable use.

The HPM model is essentially a closed-loop system with both extrinsic and intrinsic sources of feedback affecting its operation. External feedback is essentially operationally defined by KR and the previous discussions of potential innovations in our thinking about KR as stated by Adams (1978)[99] are particularly relevant. The intrinsic sources of KR are essentially response-produced stimuli from any sensory channel involved in executing the movement. The intrinsic sources of feedback also serve to give the individual information about the performance of the response <u>while it is being executed</u>. While the extrinsic feedback typically gives the performer information as to whether the objective of the response has been met.

Most important for the purposes of this report is the distinction made by the model between open skills and closed skills (not to be confused with open-loop or closed-loop theorizing). These two classes of skills are defined in terms of the environment in which they are performed. A closed skill is performed in an environment where the stimuli and cues controlling the response are static, and unchanging. Examples would be the execution of a tee shot in golf, the kick-off in football, or, for our purposes, the pushing of a sequence of buttons in response to a given display code in the AIC task. The open skills are defined as those in which the controlling environment is continually changing. Basketball, a kick-off return, or the tracking of a constantly changing visual target would be good examples of open skills. There are important considerations for the teaching of each of these types and those considerations will be presented in a later section.

An important consideration, is that of limited central processing capacity. Given that any task produces a load in the central nervous system's processing capacity, when two or more tasks are conducted concurrently they compete for this resource (Keele, 1973[54]). Moreover even within a single task the teacher should proceed from simple to more complex examples of each. Gradually, as practice proceeds the individual reaches a level of increased automaticity of responding so that the once very attention demanding task's drain on central processing capacity is reduced and more complex behavior may be efficiently undertaken.

With the distinction of open and closed skills established along with the importance of resource allocations reiterated, it may be pointed out that theoretical developments in the learning of motor skills have centered around a component analysis as discussed previously. The HPM breaks the composite into perceptual, decision and effector components. The nature of these components differ however between open and closed skills.

Open Skills.

Perceptual Mechanism. The perceptual mechanisms code, organize, and transfer the incoming information. Such information is used by both the decision-making component and the memory mechanisms responsible for storing information for later use. The perceptual problems for the performer consist of:

(1) anticipating the ways in which the stimuli will change and monitoring the target as it in fact moves through time and space;

(2) at the same time the performer has to monitor his own performance in tracking the target through an analysis of his own response behavior and an awareness of his position relative to the target;

(3) the performer must also incorporate the extrinsic and intrinsic feedback available while the response is being executed (performance feedback), and when the response is completed.

In an open skill the most important determiner of the accuracy of a response, then, is the ability to predict and anticipate what the "opponent" or target will do.

Once achieved, this ability will allow the performer to selectively attend to only a subset of the stimuli on the display, thereby reducing the load on central processing capacity, and making the "system" more able to respond to other stimuli. It will also give the performer the added benefit of a decreased response latency.

Decision Mechanism. A characteristic of an open skill is that many plans of action may be possible for any given input configuration. The goal is to decide on an appropriate plan of action to meet optimally the need of the situation.

The efficient performer will have the ability to bring the most likely plans of action or schema out of long-term, and into short-term memory. The obvious advantage of this ability is the reduction of alternative plans of action that the decision system will ultimately have to scrutinize before affecting a response, and thus a savings in execution time. The inexperienced performer, lacking either the storage of, or the ability to retrieve the appropriate subset will find himself stymied by the complex input which by definition is continually changing in an open skill task. This is essentially the pre-processing idea discussed earlier.

The major source of vulnerability to the efficiency of the system vis a vis the decision process, is of course the opponent's behavior changing while the performer is choosing, or having changed once the performer has chosen a plan of action. Ideally the performer should be able to make a fast enough analysis of the situation so as to be able to nullify or successfully react to the opponent's behavior.

Effector Mechanism. The effector mechanism may be considered to be organized both hierarchically and sequentially. The order implies that the strategy must be determined before the tactics can be initiated. The sequencing of information is also important since once the components of the plan of action are determined, their execution order must also be specified to meet the objectives of the task.

> . . . A major difference between the organization of the effector mechanism of an experienced (performer) and a novice is that the former has a number of "motor programs" at his command. Motor programs, from this point

> of view would be highly overlearned plans of action stored somewhere in the brain and capable of being run off automatically once the performer has ordered their execution. . . (Marteniuk, 1976, page 26[110])

[Note that the notion of motor programs is not universally accepted (see Adams, 1971[75]) yet it has sufficient "functional utility" to be included here.]

<u>Closed Skills</u>. There are two basic sources of distinction between open and closed skills. In the Marteniuk presentation of the HPM it is assumed that time stress generated by complex perceptual and decision processes does not typically exist for closed skills. This is certainly the case for the athletic skill of, say, a golf shot were the player may take virtually all the time necessary to prepare for the response. On the other hand, closed skills such as responding in the constant and predetermined manner to a given visual code may very well be subject to time pressures. It should be recognized then that the following HPM model may be limited in its application to time-stressed closed skills.

The second major distinction is in the demands placed upon the decision and effector components. A closed skill requires the execution of a specific plan of action when the performer is confronted with a given stimulus configuration. The flexibility and diversification required of the system in an open skill are less necesssry for the efficient performance of a closed-skill task.

Perceptual Mechanisms. While the above statements concerning flexibility, etc., are true, it is nonetheless the case that in a closed skill the performer must still process the various sources of information before executing the response, and must still attend to the feedback during performance as well as upon completion of the response. The same general requirements of the perceptual system apply for closed as for open skills.

Effector Mechanism. In a closed skill the notion of a motor program becomes even more intuitively (if not empirically) valid. It is to be considered that once the incoming information has been analyzed and classified, the degrees of freedom for response selection have virtually been reduced to zero. Only one correct course of action is appropriate and if contained in the memory system of the individual, should occur without hesitation. In Adams (1971)[75] terminology, the "memory trace" should, by a simple associative process, elicit the correct movement sequence.

However, one may hesitate to characterize this process as being purely the running off of a simple motor program. There are sufficient examples of individuals well skilled in the execution of complex sequential behavior (e.g. professional violinists, and typists) who in the midst of apparently being under the influence of a well defined motor program, still have the admirable ability to monitor their own behavior and to detect errors.

Communication. In using the HPM to develop principles for teaching some general considerations must be noted. In teaching,

> . . . the main concern is with the naive or relatively inexperienced performer who has not accumulated this huge reservoir of past experience to draw upon.

> What this means is that individuals of this type are faced with a great deal more information (that is, uncertainty) than someone with experience. The naive performer has no basis for making absolute judgments or anticipating environmental events. At the same time he has not yet established compatability between various environmental demands and their proper actions and further, has had very little practice in organizing and executing plans of action.
>
> (Marteniuk, 1976, page 29[110])

What the above essentially gets reduced to is a subject potentially confronted with huge amounts of information and not having the wherewithal to respond to them The teaching situation must be structured to limit the amount of information during the acquisition procedures. One obvious way to proceed with acquisition, then, would be to slow down the rate of presentation of information to greater than real-time intervals. This has the advantage of taking the learner slowly through the steps in the response sequence as well as familiarizing the learner with the characteristics of the sources of feedback available during and after responding.

A second obvious procedure would be to limit the complexity of the tasks so as to present them in subsets of related activities until some criterion is reached before moving on to the more complex integration of these tasks.

Perceptual Mechanisms. The first consideration is that the subject be motivated. The limited short-term memory functions dictate that new information be presented in

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such a way as to allow the learner to remember over the learning trials, relevant information about the task. The instructions too must not exceed the limited ability of the subject to remember them in initial learning trials. Amplification and expansion should come only after preliminary routines have been mastered (i.e. put into long-term storage). Of consideration here also is the degree to which a complex task should be subdivided for basic mastery. Based upon the Fitts and Posner's (1976)[111] review, one would, when confronted with the necessity to subdivide a task based upon initial perceptual and memorial limitations, arrange the components so that they are as independent of each other as possible. Components that will ultimately require a high degree of integration and interdependence should be practiced together, yet be separated from components from which they are relatively independent.

With respect to content, the teacher must, especially with open skills, instruct or prepare the student as to what dimensions or input characteristics to respond to. Thus the teacher primes the learner to anticipate the relevant changes in the input and early in training helps the learner to limit the set response alternatives relevant to a given situation.

Decision Mechanism. In open skills the teacher should make clear what the relationships are between the environment and alternative responses. This becomes more important the more complex the input situation becomes.

Effector Mechanism. Up to this point little has been said concerning the cognitive component of motor skills. Adams (1971)[75] has stated that it is difficult to consider a motor skill being acquired with the total absence of verbal control during the initial stages. The ubiquitous verbal mediation and organization that humans use, especially during early learning trials, may be made more efficient if prepared in advance by the teacher and presented to the learner. Thus, in executing a complex sequence of behavior it would be helpful to have a verbal representation of the sequencing of the responses to organize the total, more complex, response. Eventually this verbal mediator will drop out but nonetheless will be retained in long-term storage should the execution pattern for some reason break down. In other words having the verbal sequencing will expedite mastery of the task, and may even be a valuable resource in an emergency situation or high stress situation when the automaticity of responding breaks down.

The pedogogical recommendations resulting from the HPM implies any means by which the teacher can limit uncertainty in decision-making will facilitate performance in the task. Early in training this is particularly important since it reduces processing capacity utilization for decision mechanisms and places emphasis on the execution of a proper response. The goals of the behavior should be made perfectly clear to the student. This is especially important for complex behaviors where the component responses'relationships with the overall response should be made clear. Also controlled should be students' expectations of potential changes in the stimulus array. This will ensure that the student pays attention to relevant dimensions on the display. Moreover, especially early in practice, the number of events to be attended to should be restricted to allow the student the opportunity to master simpler components before moving on.

The initial steps towards achieving automaticity may begin with the instructor providing the student with a verbal outline of the plan of action for the desired movement. This mnemonic device will allow the student to store in memory a representation of the movement and its sequence that he, early in practice, could not otherwise be expected to have. The mnemonic will in particular provide a verbal step-by-step plan of action that will assure the proper sequencing of the more complex movements. Ultimately this mnemonic may not be needed as automaticity is achieved but as stated earlier, it may at sometime be a useful long-term memory resource.

The use of all forms of feedback is very important for the development of efficient motor schema. The following recommendations are made to optimize the feedback made available to the student. The feedback must be presented in a form that the student will be able to utilize. The task should be augmented so that the student, after presentation of feedback, has in short-term memory the goal of the movement, the knowledge of the outcome of the movement, the image and plan for action of the movement, and the actual way the movement was executed. These are essentially the components of a motor response that Schmidt (1975)[76] has defined as the necessary information needed to develop a motor schema, or rules for a particular movement. A final important point here is that the student should have some uninterrupted time after response execution to evaluate for himself the response just completed and the feedback received.

Instructional Strategies. It has been previously stated that skills research has lagged behind other areas of scientific endeavor in the area of learning and memory, and that only relatively recently have unifying theoretical concepts been attempted. Though the currently most popular theory (Schmidt, 1975[76]) is now several years old, it has had relatively little impact on applied research. Fortunately for the issue at hand in this report, there has been a series of experiments conducted by Singer and his associates (Singer, 1975;[112] Singer and Gaines, 1975;[113] Singer and Pease, 1976[114]) and by Prather and his co-workers (Prather, 1971;[115] Prather and Berry, 1970;[116] Prather, Berry and Bermudez, 1972[117]) that seem to relate to Schmidt's thinking.

Singer's research especially has been concerned with the assessment of instructional strategies and their effects on the acquisition, retention, and transfer of a complex motor response. His basic apparatus is sufficiently similar to the AIC console to warrant more than just a casual review here (see Singer and Pease, 1976[114] for a complete description.) The Singer and Pease study (1976)[114] serves as a general reference for their research and will be reviewed here in some detail. The task involved a computer-managed serial manipulation apparatus which required sequential coordinated hand and foot movements.

> The eight common objects (door handle, pound buttons, and various types of switches) yielded a total possibility of 19 different manipulations from which the learner could choose when making a selection for the first correct response. Four of the hand objects were wired to a foot pedal in such a way that they could operate alone or in a series

> with the foot pedal. The subject had to press the foot pedal simultaneously with the hand manipulation. From the 19 possible manipulations, 8 were selected to be programmed as a serial manipulation sequence for the initial learning program.
>
> (Singer and Pease, 1976, page 791[114])

Feedback was presented by the visual display of lights and indicated correctness of response. The sequence was changed on a subsequent transfer task. Of central concern were the effects on learning of three different types of learning strategies, with male and female undergraduate subjects aged 17 to 25 years being randomly assigned to treatment conditions.

All subjects studied a written description of the sequence two minutes before learning commenced. The "guided" learning group received prompting in the form of a visual display of a number corresponding to the next object to be manipulated, as well as verbal cues (not defined in the study) by the experimenter. The "discovery" or what Prather has called in his research, the "trial and error" group, received neither cues nor prompts. Finally, a combination group received prompting and cueing for the first four trials but nothing for the remaining 16 trials of acquisition. All groups performed 20 trials of the task.

The next day subjects returned for a retention test on the initial sequence with no cuing or prompting for any group. There then followed a short relearning phase to establish uniformity of responding, followed by a transfer task of 16 trials administered to all subjects using the "discovery" method.

The following results were obtained. Subjects on the "guided" task mastered the initial task faster than any other group. However, the two groups with some discovery experience evidenced superior and equal retention to the guided group, and superiority to the guided group in earlier stages of the transfer task. The authors stress that the inclusion of a "discovery component" will create a more flexible motoric representation that will benefit the subject not only on the specific practice task but on related ones as well.

The implication of these data for open skill tasks is that subjects should be presented with a variety of stimulus situations and have the opportunity to respond in a variety of ways at some point during practice. Though Singer and Pease introduce discovery later in training for the mixed condition, the effects of an initial discovery period followed by guided learning remains to be determined. Thus, the optimum sequencing of discovery and guided learning has yet to be decided.

These data fit nicely with the requirement that open skill tasks be learned with the subject being aware of different response possibilities (plans of action) and is in agreement with the conclusion of the several researchers (mentioned earlier) who have investigated Schmidt's theory and who have found superior learning and transfer with variability during acquisition.

TOWARD A THEORY OF THE EXPERT AND NOVICE

If we could aggregate the important features of the three controller tasks (GCA, LSO, and AIC) into a single hypothetical controller's role, we may find that the differences between the expert and novice can be described quite well in light of the recent basic research and theory just discussed. Consider, if you will, this composite controller, seated at a console monitoring a display which presents a continuous flow of visual input with intermittent auditory input over a headset. The visual events are predictable with experience, but some of the visual cues can be quite subtle and will require much practice in order to perceive them. Information load and processing demands will be quite heavy at times as there may be simultaneous visual inputs--not to mention auditory inputs--concurrent with verbal and motor response requirements. Some of the responses may be associated with a single visual input but most of the responses are to be elicited by a complex combination of events. The responses themselves vary from simple to complex constructed verbal responses and sequenced motor responses.

Expert

Perceptual. In describing the expert's perceptual skills, we could describe two possible situations. The first is that the perceptual schemata by which the subtle cues are picked up are unitized. Through extensive practice, the expert automatically codes the features. The second possibility is that the predictability of the visual inputs leads the expert to activate schemata in anticipation resulting in detections with very short reaction times.

Needless to say, both the automaticity and expectation explanations may be correct to some degree. (See page 58).

Visual Search. Because of the rapidity with which the visual inputs are coded, as described above, additional simultaneously presented inputs do not appreciably increase processing load as though they were processed in parallel. In the case of divided displays, expectations lead to efficient scanning responses.

Memory Search. The inputs are compared with a number of events for which the expert is looking. The comparison process has become automatic to the point that the number of events for which he is searching no longer effects search rates.

Response Selection and Construction. First, simple structures are unitized such that a specific visual input automatically elicits the appropriate response. Secondly, those response selections dependent upon a complex combination of inputs may be helped by pre-processing. As an example of this pre-processing, look at Figure 16 wherein the expert is to compute a final heading to be given to the pilot. Instead of waiting until the heading is needed, he anticipates its need by processing information during a preceding advisory. Thus while in the act of giving an elevation advisory for example, he notes that the last heading given was 160°, the aircraft is within five miles of touchdown, and there is a crosswind with which he must reckon. Noting all of this, he pre-selects two possible headings. If the pilot is late and will overshoot the azimuth, a correction of 164° is to be given--otherwise

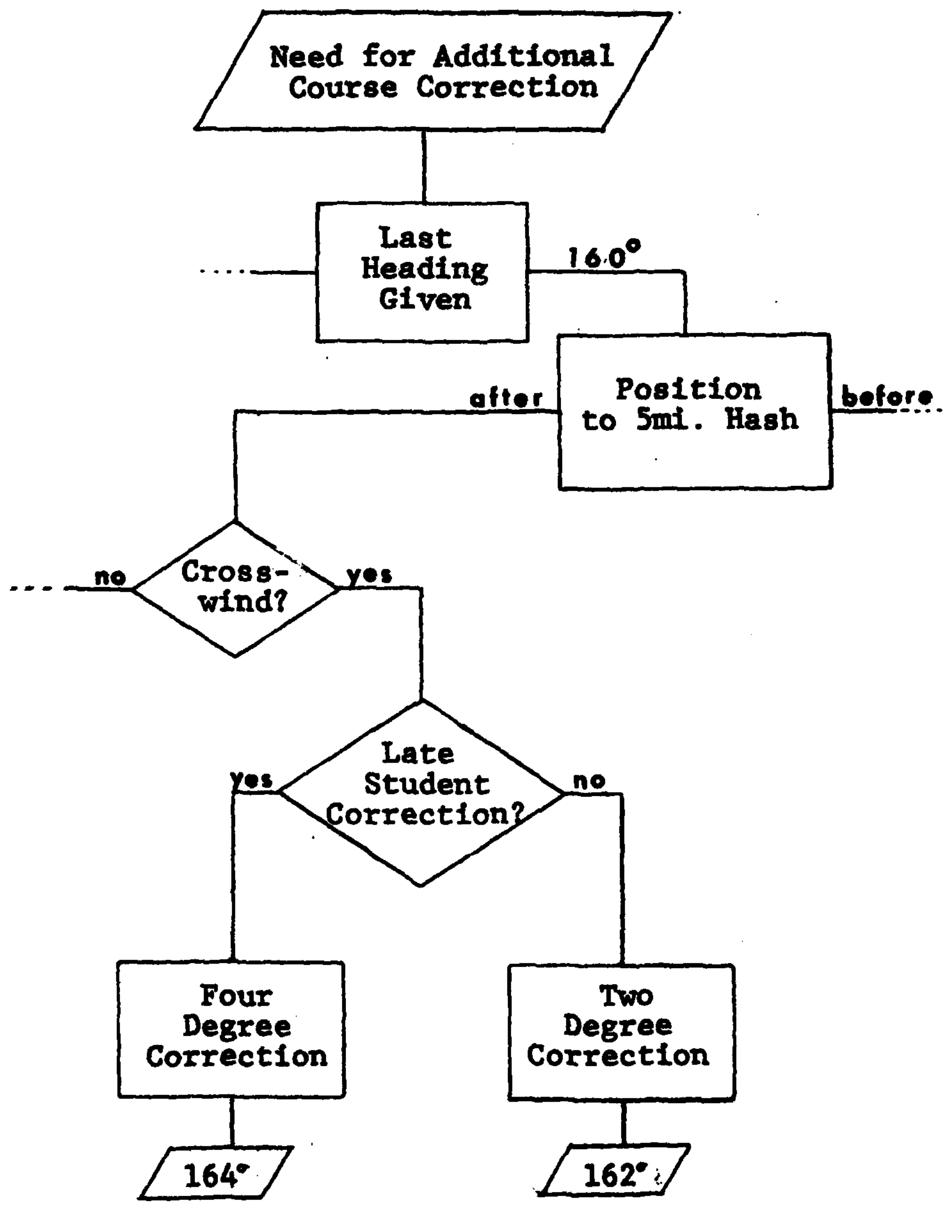

Figure 16. Schematic Diagram of an Example of Preprocessing

162° will be given. These two headings may be held in short-term memory until the requisite visual input is received by which the controller will select and execute one of the two advisories. Without the preprocessing, when the requisite visual input is received, the controller would have to begin at the top of the diagram in Figure 16 and must invest resources and time between the onset of the visual input and the output of the response.

This form of preprocessing (similar to that reported by our expert PAR controller) is a likely description for the expectation mechanism. Unanticipated events (e.g. the pilot reacting early instead of late) would require a heading response not held in short-term memory. Thus the expert would either give an error or have to go through time consuming reprocessing to select a response.

Thirdly internal schemata have been modified over the lengthy time the expert has been functioning in his capacity. Desriptions are so finely tuned that mismatches rarely occur. Parts of the knowledge structure have been reformulated such that needless steps in processing have been eliminated so that now the resource allocation functions look like "D" in Figure 8.

Response Execution. For closed-skill tasks, the expert has well established "motor programs" upon which to draw. He can predict the sequential steps in the overall monitoring situation and is waiting only for the necessary information to trigger the particular program sequence. The task has been mastered to such a level that little in the way of resource allocation is needed. Most of whatever resources are required in motor responding are given over to the open-skill tasks which require constant monitoring.

For the open-skill task of tracking a target on a continuously changing display, the expert has had enough experience to predict certain general types of target changes. The expert will vary the amount of processing capacity given to the task as a function of the total current state of the operation and the importance of the tracking task on the overall execution of the task. As the situation becomes more crucial, the expert must transfer more processing capacity to the tracking task, and must retrieve and keep more of the alternative plans of action in short-term memory to keep the system flexible.

Thus the performance of the expert, for the most part, can be said to be in the data-limited region. What automatic processing exists makes him quite rigid in terms of any reversals or modifications that might be required in retraining. His automatic detection skills also make him highly susceptible to distraction if told for some reason to ignore certain inputs. Because of his reliance on expectancies, unexpected events will throw him--requiring that he process, displaying increased investment of effort. Finally, because he is now a resource-efficient system, he does not display problems of holding certain information, such as the last heading given in short-term memory. He has plenty of time and resources left for the recycling of temporary information.

<u>Novice</u>

Perceptual. In his novice state, he is now said to be in either the feature discovery stage or the coding stage of perceptual learning. Here, the act of learning itself, e.g. the search, discovery and testing of features, requires an investment of resources, additional to that required in the task. Thus the resource allocation acquisition function would be similar to that shown in Figure 11. At the beginning stages of perceptual learning, the process may be data-limited in that regardless of how hard he tries, the novice LSO for example may not be able to estimate the pitch of the aircraft because he had not identified the relevant features. Later the process becomes resource-limited in that (in knowing the relevant features) he must invest resources in scanning the visual array of features in order to code it. Finally, the process becomes data-limited again as the coding becomes automatic and requires little resources.

Visual Search. The search of the visual inputs is a controlled search for the novice and requires extensive resources. With the display divided, he anticipates little, showing inefficiency in his scanning behavior.

Memory Search. Again, the student is engaged in controlled processing instead of automatic processing. The search itself consumes time and resources. Targets are missed because of:

(1) time constraints (the amount of time available for detection is shorter than that required by controlled processing at a given level of resource investment,

(2) resource limitations (because of competing concurrent tasks with perhaps higher subjective utility values, the amount of resources available for investment is deficient),

(3) mismatch as between target and memory representation (primitive schemata, not yet finely tuned, may not be general enough for detection of variable real-world targets).

Response Selection. Not having the experience to anticipate events, the novice seems to do little preprocessing. Using the example shown in Figure 16, instead of pre-computing the two possible headings of 164° and 162° in anticipation of the need, he only computes the required heading as the need presents itself. Thus there is a long latency between the onset of the need for the response, and the actual production of the response. If there is too little time for this multistep processing, either the response will be omitted, or certain steps will be omitted with default values assumed (e.g. assume no wind and make no reference to the five mile hashmark defaulting to the five-degree minimum course change rule) resulting in an error response (e.g. his choice might be between 165° and 160°).

The novice has only rudimentary motor programs for the execution of closed-skill tasks. Responses that the expert can make almost unknowingly (without resource), the novice must not only take time to retrieve and decide upon, but most likely take time to execute as well. The obvious drain on resources detracts from those components of the task requiring larger investments, keeps the novice from "keeping up" with the real-time situation, and in an overall sense, decreases the efficiency of the system.

The novice does not have the developed memory ability to preselect response patterns for a recognized subset of alternative target behaviors. The novice maintains an awkwardly large memory set, often of actually irrelevant material. Unlike the expert who can, with confidence, limit the size of the set of alternative plans of action, the novice gingerly holds on to plans of action even though the expert would long before have deemed them as "unlikely occurences," and would have precluded them from being a drain on resources.

Thus the novice, for the most part, functions in a resource-limited domain. He is characterized by controlled rather than automatic processing. He handles high frequency events as well as rare events, because he has not built up any expectancies and he does not engage in much preprocessing. Because he is in controlled processing and not automatic, he is quite flexible regarding reversals of contingencies and training modifications in general. Since he is characterized by time and resource consuming controlled processing, he becomes overloaded easily and may lose information from short-term memory because his resources were diverted from any recycling process.

Having described the expert and novice in terms of current research in cognition, the next task becomes one of reviewing current developments in training. The next section reviews recent developments in CAI, primarily regarding the representation of knowledge and tutorial strategies. Most of the developments have not dealt with time-sharing tasks (a point we will want to address later), but show promise in their particular approach taken, particularly the utilization of artificial intelligence in CAI.

DEVELOPMENTS IN CAI

Computer assisted instruction (CAI) has come a long way since the early 1960s. Its development has been influenced by basic research in cognition, artificial intelligence, and linguistics. The recent history of CAI has been described by Lacey (1977)[118] McLagan and Sandborgh (1977)[119] and Suppes and Macken (1978).[120] Feurzeig, Cohen, Lukas and Schiff (1975)[121] provide a review on research development in adaptive training. Early programs in CAI were developed at the Institute of Mathematical Studies in the Social Sciences (IMSSS) at Stanford (see Atkinson, 1968;[122] Suppes and Morningstar, 1972[123]) the University of Texas at Austin, (see Judd, Bunderson, and Bessent, 1970[124]), Florida State University (see Hagerty, 1970[125]) and of course the University of Illinois wherein the well-known PLATO system was developed in connection with the National Science Foundation and the Control Data Corporation. The initial results of CAI met with mixed results when compared with traditional instruction (see Vinsonhaler and Bass, 1972[126]). Early 1970s brought widespread use of authoring languages such as Coursewriter developed by IBM back in the early 60s, the use of minicomputers and television technology such as the TICCIT system developed by the MITRE Corporation, and the introduction of artificial intelligence in CAI by Bolt, Beranek and Newman, Inc. Recent trends have been toward miniaturization, the development of intelligent, knowledge-based systems with natural language capabilities, and speech recognition/production (see Atkinson, 1978[127] regarding CAI in the future).

Of all the developments in CAI, those of greatest possible impact on future automated-speech-based training systems would be: (1) knowledge representations, (2) optimization techniques, and (3) natural language capabilities. (It goes without saying that the speech recognition technology itself would be of utmost importance.) The sections that follow will attempt to describe developments in the representation of knowledge and natural language processing. Chatfield and Gidcumb (1977)[37] provide a review of optimization techniques which will not be reviewed here.

REPRESENTATION OF KNOWLEDGE. The goal of research efforts in CAI, even back in the 60's was to develop systems which would give the student some amount of initiative in the process. Bryan (1969)[128] developed a taxonomy by which he categorized the developments in CAI in terms of the amount of initiative the student could take with the system. The first category in which the student was allowed the most freedom was referred to as <u>ad lib</u> CAI. Here the student is given full control of a library of routines which he uses at will. An example of this was <u>LOGO</u> developed by Feurzeig and Papert (1970).[129] The second category consisted of games and simulation wherein the student was allowed an intermediate amount of initiative. An example of this was the Socratic system by Swets and Feurzeig (1965).[130] In the last category the student was maximally constrained by simply being given a preconceived series of frames with Crawderian branching as the only novelties in student trajectories through the curriculum. These deterministic frame-based systems have been variously referred to as script-based CAI and ad hoc frame-oriented (HFO) systems.

Since Bryan's review, developments in CAI have produced mixed initiative, generative systems employing techniques from artificial intelligence (AI). The research by Jaime Carbonell (1970),[131] funded by ONR, could be said to be the turning point in this direction. Carbonell sought a mixed-initiative discourse between the student and the system. It was easy enough for the script-based systems to query the student, but not vice-versa. To enable the student to query the system two requirements must be met:

(1) the system must be able to understand semantically as well as syntactically, novel natural-language-type inputs on the part of the student,

(2) the system must somehow have incorporated the knowledge of the expert so that it can "generate" responses.

At the time, the products of basic research efforts in AI (especially from the MIT Lab) had begun to impact both areas. Bobrow (1964),[132] Simmons (1970a),[133] (1970b)[134] and Simmons and Silberman (1967)[135] had carried out research on natural language communication with computers, while Minsky (1968)[136] and others mentioned previously had worked on the problem of representing knowledge in the computer.

Carbonell (1970)[131] developed a training system called <u>SCHOLAR</u> which was used to teach geography. Instead of the script based frame oriented methodology, Carbonell developed a <u>semantic network</u> of declarative facts comprising the knowledge domain. A schematic drawing of a portion of the network would be represented by Figure 17. Associated with each concept is a list of descriptors. The descriptors include such things as the: super concept, examples of the concepts, locations or other detail of specification, etc. Note the linkages between concepts. It is possible that

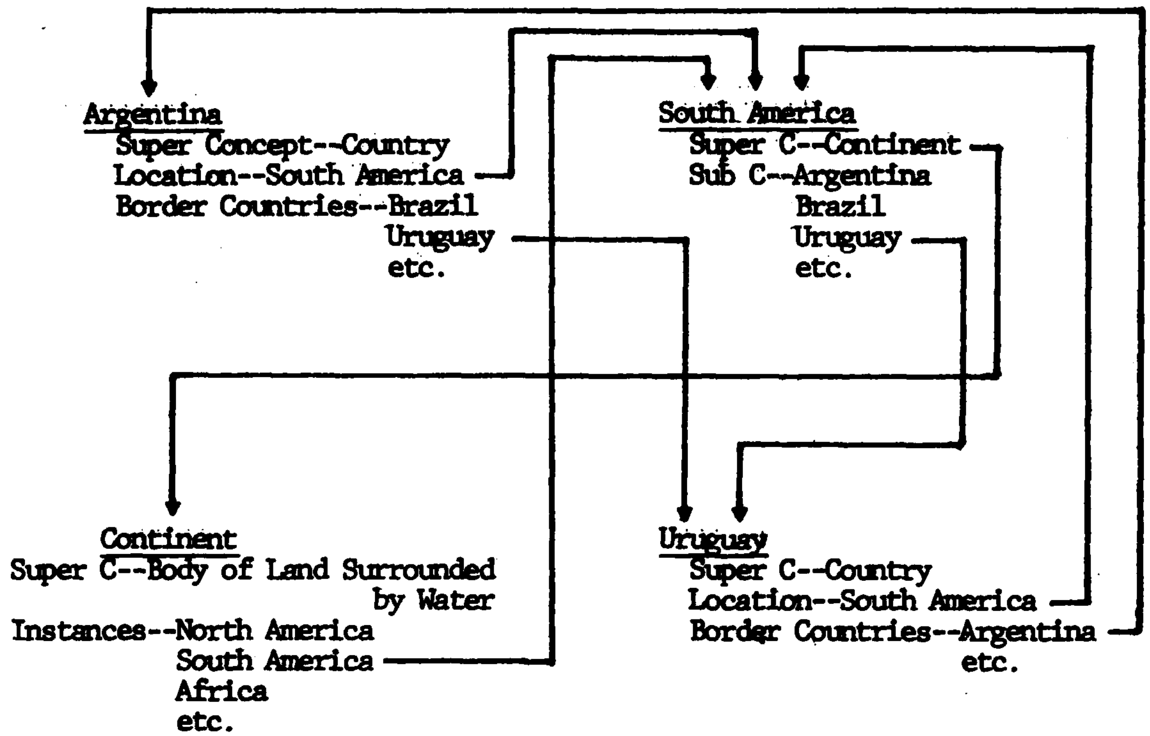

Figure 17. Example Knowledge Structures in the SCHOLAR System

some of the items listed under a concept may themselves be concepts in the knowledge domain. Thus the information which was to be taught was represented as a semantic network similar to proposals of the representation of knowledge in humans as described previously. Using this information, stored as a semantic network and its natural language capabilities, SCHOLAR would generate questions and answers for the student. An example dialogue between SCHOLAR and the student is given in Figure 18 and is taken from Carbonell (1970, p 192-193).[131] Phrases printed in uppercase are from SCHOLAR, with the student's responses in lowercase and an asterisk to the left.

```
 THE LANGUAGE IN BRAZIL IS PORTUGUESE.
 IS IT TRUE THAT THE CAPITOL IN BRAZIL IS BRAZILIA?
*yes.
 THAT'S FINE.
 APPROXIMATELY WHAT IS THE POPULATION IN BRAZIL?
*60000000.
 APPROXIMATELY TRUE, BUT A MORE EXACT VALUE IS 70000000.
 WHAT IS BRAZIL?
*tell me something about Peru.
 WAIT A MINUTE.  I'M CHECKING MY FILES.
 LET'S PROCEED NOW
       PERU IS A COUNTRY.
       IT IS IN SOUTH AMERICA.
          .
          .
          .
       THE CAPITOL IS LIMA.
 NOW ANSWER THE QUESTION YOU DIDN'T ANSWER BEFORE.
*q/a.
 DO YOU WANT TO CHANGE THE GENERAL MODE OF THE INTERACTION
 TO Q/A?  YES OR NO?
*yes.
 O.K.  MR. JONES.  LET'S GO AHEAD.
*please tell me more about Peru.
       THE AREA OF PERU IS APPROXIMATELY 480000 SQUARE
       MILES.
       THE LANGUAGE IS SPANISH.
*how many square miles in Brazil?
       THE AREA IS APPROXIMATELY 360000 SQUARE MILES.
*what is the principal religion in Uruguay?
 .
 .
 .
*could you please indicate the principal rivers in
 Argentina?
 I DON'T UNDERSTAND YOUR WORD "INDICATE."  I'LL GIVE YOU
 ANOTHER CHANCE.
*the principal rivers in Argentina are ________?
 THE PRINCIPAL RIVERS IN ARGENTINA ARE THE RIO DE LA PLATA,
 THE PARANA, . . .
```

Figure 18. Example Dialogue Between a Student (*) and SCHOLAR (CAPS)

Note first that the student is able to query the system by typing a question in place of a response. SCHOLAR had asked what Brazil was. The student simply responded by asking SCHOLAR to tell him <u>something</u> about Peru. He was not specific about what it was he wanted to <u>know</u> about Peru. The system's natural language capabilities allowed it to recover from an unexpected response, comprehend the message, and be able to formulate an intelligible answer. To get the information, it had to access the semantic network. Note that the system's output is similar to the internal representation stored in the network. In the event that the student's query was not understood, the system asked the student for a rephrasing of the question. The system obviously only has a limited vocabulary and can only communicate in a subset of the English language. The student would soon be able to restrict his vocabulary however, as he gained experience with the system.

The purpose behind a system like SCHOLAR is to develop an executor program which could transcend various subject-matter domains. The executor for the teaching of South American geography for example could be used to teach European geography. In a sense, the executor is a model of the instructor, while the knowledge domain represented in the semantic network is a model of the expert. The set of declarative facts represents the knowledge of the expert which the student is to acquire. At any point in training the student is modeled as a subset of those facts. The executor, or model instructor is to present new information or facts from the expert's set which are not included in the student's set. Further, the model instructor is to analyze and diagnose errors and misconceptions in order to ascertain the status of the concepts in the network. The following is an example taken from Carbonell (1970, P.199).[131]

> "Suppose a student has been told that the language in Argentina is Spanish, but when asked about the language in Buenos Aires, responds: 'Portuguese.' Three hypotheses can now be made about the student's misconception. He may have forgotten what the language in Argentina is, he may not know that Buenos Aires is in Argentina, or he may not be able to draw the inference that the language in a country is usually the language in the cities located in that country."

With follow-up questions to the student, the executor can reduce its uncertainty about the causes of the student's error and present remedial information or represent the concept, which it had presumed was learned, as being in an unlearned state and return to it later.

A more recent effort funded by ONR was the development of the FLOW tutor and is reported by Gentner and Norman (1977),[137] Norman and Gentner (1978),[138] Norman (1979),[139] and Gentner (1979).[140] The FLOW tutor represents its knowledge domain as schemata and prototypes (Bobrow, Kaplan, Kay, Norman, Thompson and Winograd, 1977;[141] Minsky, 1975[63]) as described earlier. The structural units themselves are commands and statements of the FLOW programming language instead of geographical facts as in SCHOLAR. The FLOW tutor works much like SCHOLAR in that the knowledge base is an "expert" and the student can be characterized as an incomplete collection of independent schemata all wanting to "fulfill" themselves. Associated with each schema is some internal intelligence with completion as its goal. Coordinating the independent structures is an agenda. The agenda is a list of incomplete schemata petitioning and waiting for attention in order to complete their parts.

Brown, Burton and Zdybel (1973)[142] developed a system called SOPHIE which tutored students in electronic trouble-shooting. The student's trouble-shooting hypotheses were compared with that of a model of the expert. The knowledge was represented in procedural form rather than a network. The logic of the system was to move the student in the direction of the model of the expert. More recently, Brown and Burton (1977)[143] developed a system called BOGEY, based on the building of a procedural model for the development of a student's arithmetic skills.

BIP-II, developed at Stanford, is another network-based system designed to teach skills in BASIC programming. The knowledge representation is described as a Curriculum Information Network (CIN). An earlier version of a CIN-based system (BIP-I) is described by Barr, Beard and Atkinson (1976)[144] with the BIP-II enhancements described by Wescourt, Beard, Gould, and Barr (1977).[145] In BIP-II the CIN was developed around skills rather than a network of declarative facts, and utilized additional types of linkages between nodes. The curriculum of BASIC statements was first organized into a network called BASICNET. An example portion, taken from Wescourt et. al.[145] is shown in Figure 19. The nodes themselves represent conceptual entities regarding BASIC statements while the links between nodes represent relationships between the entities. The nodes and links were then coded in a list

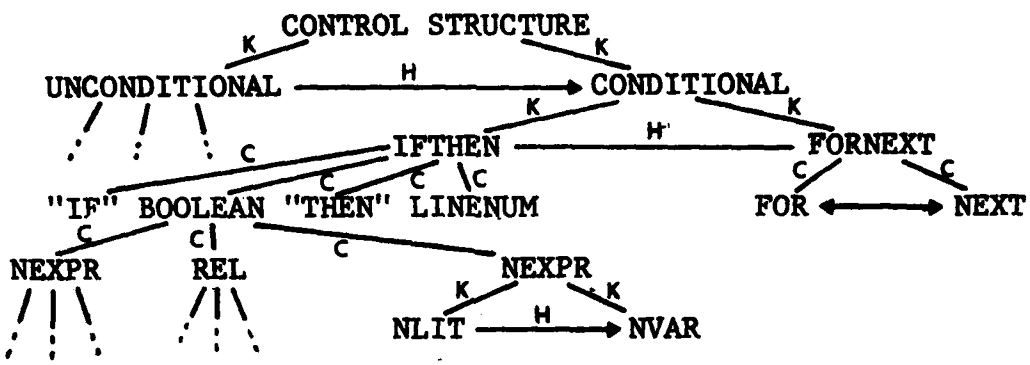

Figure 19. A Portion of BASICNET Where the Links Between Modes Represent Kind, Component, Hardness, etc.

notation for the computer. Examples of such listings would be:

(CONTROLSTRUCTURE K (UNCONDITIONAL CONDITIONAL))
(CONDITIONAL K (IFTHEN FORNEXT))
(IFTHEN C (IF BOOLEAN "THEN" LIMENUM) H (FORNEXT))

From these three listings from three different levels in the network, it can be seen how the conceptual entities can be represented.

In addition to the BASICNET, a second network of skills was constructed which reflected the first network. As an example, a "conditional branch" skill (number 42 in the listing) was represented as follows:

(SK042 (IFTHEN (BOOLEAN . (NEXPR . NLIT)(NEXPR . NVAR))))

This was a listing of a skill in using IF THEN statements between a numeric literal and numeric variable with the relation unspecified. Other instances of essentially the same skill could then be described relative to the first. As an example, skill 46 was the same as 42 except that the relation was between two numeric variables instead of a numeric variable and a numeric literal. It was represented as:

(SK046 (SK042 (NEXPR . NVAR)))

Note that the listing of 47 refers to 42. Skill 42 along with its other "IFTHEN" instances comprised in a skill set of which there were ten such skill sets in all.

Within a skill set, relations between pairs of skills were established by referring back to the BASICNET. In the following example:

(SK042 H (SK044 SK046) A (SK047) P SK003))

Skill 46 (and 44) is judged to be harder than 42, as shown in the link between NLIT and NVAR at the bottom of Figure 19. Note further that skill 42 is said to be analogous to 47 with skill 3 as a prerequisite. These latter two relationships or links are not shown in Figure 19 because of its brevity. The list of linkages between skills in LISP notation comprised what Wescourt et.al.[145] termed the SKILLSNET.

The learning of the skills was represented as a five-state learning process, the states being (1) unseen, (2) seen but experienced trouble, (3) marginal, (4) unseen but rated as easy to learn, and (5) learned. Briefly the task selection logic was to create a set of skills occupying the lowest learning states, remove the skills having unlearned prerequisites, and then select tasks (programming problems) that involve the designated skills. Since each of the selected tasks may vary as to their ratio of learned to unlearned skills of which they are comprised, the actual task selected would depend on the history of the progression of the particular student.

BIP-II is of interest not only in terms of the way knowledge or skills were represented by also by the types of linkages between nodes and the procedure for generating programming tasks for the student. The links not only represented semantic links but also analogies, generalizations, prerequisites, and relative difficulties. Thus tasks generated to build new knowledge could take into account the nature of the knowledge already acquired. For example, the printing of string literals can be presented as being analogous to the printing of numeric literals with which the student may already be familiar. The importance of presenting new information in terms of old, has been discussed in previous sections and by Norman and his colleagues.

As mentioned previously, the training systems presented thus far base their student model on a representation of the expert. They view the student as a set of facts or skills which is a subset of those presumably possessed by the expert. Goldstein and Carr (1977)[146] have termed such models as "overlays" to emphasize that the characterization of the student is a derivative of the expert. In their view, these overlays suffer from the lack of any representation of a maturing process. That is the conceptual entities or skills which the student is to acquire is represented in the nature and refined form of the expert. As an example, when the student is first introduced to the concept of linear regression, he has a rather simplistic view of it. Later he learns that the concept can be generalized to non-linear regression. As Norman (1978)[73] puts it, the student goes through periods of restructuring and tuning. The importance of this is that the concept of linear regression that the student acquires is only an immature version of the concept held by the expert. Thus the network representation of the knowledge domain ought to represent epistomelogical considerations.

Goldstein (1979)[147] presents a tutor for the game of Wumpus called WUSOR-II. It evolved from the WUSOR-I version reported by Stansfield, Carr, and Goldstein (1976).[148] The Wumpus game, for those not familiar, is a game wherein the player is placed somewhere in a warren of caves. His goal is to go blindly from cave to cave seeking to slay the Wumpus while avoiding the dangers of pits, bats, and of course, the Wumpus itself. The player can make inferences about the contents of a cave by hearing the squeaks of the bats, smelling the Wumpus, and feeling a draft from the pits. Adding to this his memory for past caves he has tried, his knowledge then is a set of rules, procedures, and logical inferences that he must learn.

The distinction of WUSOR-II is that it employs what Goldstein calls a "genetic graph" to represent knowledge. The idea of the genetic graph is that it attempts to capture the evolutionary process by which a mature set of procedures evolve. In Figure 20 it can be seen that the nodes representing the rules are linked by relationships of evolution. In the example, all the rules shown evolve from rule <u>A</u> which was learned initially. Rule <u>AB</u> is said to be a refinement of rule <u>A</u> while rule <u>ABC</u> is a version that is refined still further. Rules <u>ADD</u>, <u>AdD</u>, and <u>adD</u> can be viewed as more general (or more specific) versions of rule <u>AD</u>, and are analogous to each other.

One advantage of the genetic graph is that it represents the student's knowledge at various stages. With this representation the system would not present rule

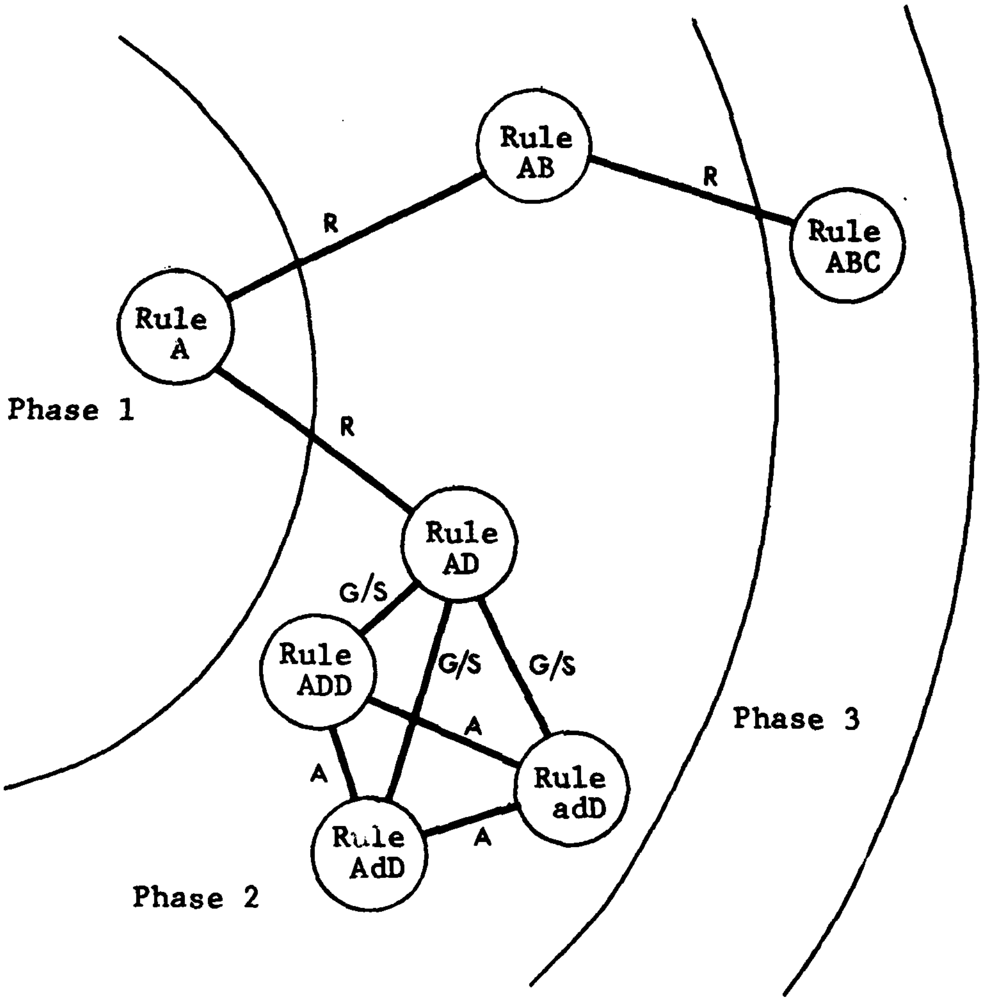

Figure 20. A Portion of a Genetic Graph Showing Genetic Links of Refinement (R), Generalization/ Specification (G/S) and Analogy (A)

ABC without first going through the versions (A and AB) at the first two levels. The difference between this and the prerequisite links shown in BIP-II is that rules A, AB, and ABC are all essentially the same rule, differing only in refinement, whereas prerequisites refer to a mandatory order relationship between different rules. An example of the evolution of a rule might be the case where a teacher tells the student the primitive form of the spelling rule "i before e" and later modifies it with exceptions such as "i before e except after c." Thus the genetic graph gives the system information as the maturity level with which a rule should be given.

A second advantage is that it would provide the system with a means by which it can present new information in terms of previously learned rules. Take for example rule ADD in Figure 20. This rule could be presented to the student as a generalization of rule AD, as being analogous to rule adD or being analogous to rule AdD providing that these other rules were already known. Thus the genetic graph provides the potential for a very powerful means by which the system can make use of prior knowledge in generating multiple styles by which a rule could be presented.

As can be seen, the knowledge representation system (KRS) is basic to a generative system with mixed initiative capabilities. Only if a system can generate tasks, questions or responses to student queries from an appropriately represented knowledge domain, can it possess the flexibility required to provide truly individualized instruction as would a human tutor. The way in which the knowledge is represented is important for several reasons:

(1) Since the ultimate goal of the system is to move the student in the direction of the representation of the expert, the KRS should be sufficiently rich to have incorporated all the essential features of the expert's knowlege and skills.

(2) An understanding of the representation of knowledge in the human (both student and expert) is essential for the

development of pedagogical techniques for the building, restructuring and tuning of knowledge structures.

(3) As portrayed in Goldstein's genetic graph, the KRS should be sufficient to represent evolutionary stages especially if the methodology is to be extended to the training of time-sharing tasks.

(4) Multiple modes concept presentation based on the student's current knowledge should be implied from the KRS, as in the example of presenting a concept as an analogy, or a generalization of another concept.

(5) Finally, the KRS should be complete enough to allow the system to generate output in natural language format.

Space limitations do not allow for a detailed discussion of the more technical aspects of representing knowledge. Readers currently engaged in the development of training systems should consult the sources cited along with Bott (1979)[66] and Bobrow and Winograd (1977)[149] concerning a knowledge representation language.

NATURAL LANGUAGE CAPABILITIES. The natural language capabilities of an intelligent system are inexplicably correlated with the representation of knowledge. Most of all the well-known systems cited thus far have limited knowledge domains such as: electronic trouble-shooting in SOPHIE, a programming language in FLOW and BIP-II, arithmetic skills in BOGEY, and tactical and inference skills in WUSOR. The result of limited domain is limited actions, concepts and constrained terminology and phraseology. This would certainly be true for aircraft-controller type training systems.

Burton and Brown (1979)[150] describe four properties that are imperative for a natural language processor: efficiency, habitability, the ability to shape the student's phraseology and tolerance for ambiguity. <u>Efficiency</u> refers to the system's ability to parse the student's query, understand it, deduce or calculate an answer for him followed by the generation of the response. All this must be done under a two second response time to avoid affecting performance (see Miller, 1968[151]) and well under that to operate within a real time aircraft controller environment. <u>Habitability</u> refers to the system's ability to understand and operate in a large enough subset of the natural language to be useful. System capacity will prohibit the size of the language subset, both now and in the near future, but the subset should be large enough to handle a large portion of the student's self-initiated responses within the constraints of the subject matter.

Consistent with the requirement of habitability, is the requirement that the system be able to reduce the student's variations in phraseology throughout the training sessions to be able to reduce the amount of times the system has to ask the student to rephrase the question. The fourth requirement is that the system be aware of <u>ambiguity</u> or multiple deep structures for a given surface structure as in the phrase, "Was the Wumpus believed to have been killed by Fred?" Here the student could be asking if Fred killed the Wumpus or if Fred believed that the Wumpus had been killed. Recognizing the ambiguity, the system could take steps to resolve it. Not recognizing the ambiguity, the system could possibly generate an answer in reference to one of the two meanings and get into a series of misunderstandings with the student.

To achieve these goals Brown and Burton (1979)[150] discuss the use of semantic grammars as opposed to the older syntactic grammars (see Simmons, 1970[133] for a review of early language processors). Using semantic processing they report that the system requires less than 200 milliseconds cpu per question from the student. Part of the success in processing rate comes from the use of semantic information during parsing for predictive purposes. For example after a noun phrase and verb phrase have been parsed in a top-down, left-to-right manner, the object of a subsequent prepositional phrase can be anticipated. This anticipation can reduce the amount of any lexical search any grammatical ambiguity, and aid in the determination of referents for pronouns. This predictive process is of interest in its own right as a result of the possibility of the human aircraft-controller using a similar preprocessing and predictive process in the anticipation of events on the display.

Many of the intelligent systems discussed implement their language processing capabilities with LISP (see Teitelman, 1974[152]). LISP is compilable and was used initially with SOPHIE. Later a compilable version of a semantic augmented transition network (ATN) was developed at Bolt Beranek and Newman (see Burton, 1976[153]) and used. The ATN process (a notion first introduced by Chomsky) has advantages over LISP. Space does not permit a full discussion of the technical details between the two here, but the sources are quite worthy of further scrutiny. Future developments of the use of ATNs at Bolt Beranek and Newman and other sources of research in natural language processing should be monitored closely.

SECTION IV

INSTRUCTOR MODEL: PRELIMINARY CONSIDERATIONS

A full development of an instructor model is premature at this time. As we will attempt to show, there are certain technological gaps which need to be filled before a complete model of the instructor for automated-speech based training systems can be constructed. In the sections to follow, we would like to make use of the basic research developments just reviewed in order to propose directions which the instructor model development should take. In outlining these characteristics, the characteristics of the traditional human instructor need to be kept in mind for reference purposes. Finally the technological gaps precluding the current implementation of such a model need to be discussed.

CHARACTERISTICS OF THE HUMAN INSTRUCTOR

The instructors of aircraft controllers are skilled controllers themselves, and may in some cases be pilots. Thus the first characteristic we would have to make would be that the instructor in most any subject matter carries an internal knowledge base. Secondly, he possesses knowledge about relationships between the event-driven tasks. He knows that having the students work on skills pertaining to certain concurrent tasks causes confusion early in training. Thus in addition to a factual knowledge base, he may have a knowledge base regarding the dynamic effects of task concurrence.

Thirdly, the instructor has experience in instructional presentation techniques. As an example, it is often heard that certain experienced instructors have excellent techniques or skills in getting information across. Some instructors have developed effective skills in the use of analogies for making the student attend to specific features, while other instructors may have developed techniques requiring students to verbalize differences between similar events as a means of getting them to attend to the relevant features that would support differentiation. Thus through experience, the instructors have acquired a repertoire of tutorial skills and procedures.

The fourth characteristic is that the instructor's natural language capabilities support mixed-initiative dialogue during the course of instruction. He is able to generate statements for the student as well as to understand and to respond to student-generated queries.

As a fifth characteristic, it should be pointed out that the human instructor has a limited capability and an intuitive desire for diagnosis. When an error is made the instructor will be found asking the student, "Why did you do that?" or, "What was your thinking at the time?" The instructor may even manipulate the student's task somewhat in an effort to diagnose the student's problem. The diagnosis is then followed by remediation. If it were ascertained that the student erred because of a misconception, the instructor then attempts to redefine the concept.

A sixth characteristic is that the instructor has an intuitive, if not formal, set of performance measures by which he is constantly assessing the student's progress. These measures may be informal and unsystematic, but he still makes use of them, even if they are only comprised of facial expressions of confusion or insight.

The seventh characteristic is that he imputes a subjective utility distribution over the points in the knowledge and skills domain. Certain parts of the domain are thought to be more important than others and this affects the distribution of his instructional efforts.

The order and extent of these instructional efforts determine his eighth characteristic, the design of the curriculum. Though the instructor possesses the intelligence to simply react to student initiatives, he generally takes the initiative during most of the instruction and imposes a curricular structure on himself. This curriculum is a product of past experience and serves as an aid in ensuring the breadth of his instructional coverage as well as a memory aid on preconceived order constraints on topics. The curriculum then serves as an external supplement to his internal representation of the knowledge domain.

A final characteristic is that the instructor is continually revising his approach. Through additional experience he revises his curriculum, his subjective utility estimates, performance measures, diagnostic skills and remediation techniques and his whole pedogogical approach in general.

THE INSTRUCTOR MODEL

Consider for the moment that there are no limits in research and development resources, and that development monies exist in great quantities. With no constraints, we could then ask ourselves what we would like to see in an automated model of the instructor. What are the possible features that an intelligent training system could incorporate, based on the reviews of the current developments in basic research just presented? Following an outline of the possibilities, we can then come back to reality and examine the effects of cost and resource considerations in development.

At the outset, we could say that an intelligent system with considerable flexibility, would be desirable. The system could follow a curriculum overall but would be locally generative within segments of the total syllabus. It would possess a student model of developing knowledge and skill structures, and diagnostic capabilities with generative techniques for remediation. Natural language communication would be needed to support mixed-iniative discourse with the student as well as an articulate interface with human supervisors. Finally, the system, with or without human intervention, should be able to modify itself as it gains experience from repeated samples of student population.

For illustration purposes, let us assume that the model instructor to be developed is to be incorporated in an automated training system designed for our composite controller task. It will be recalled that the composite task was a hypothetical aggregation of the three roles of PAR controllers, LSOs and AICs contrived for explanatory purposes.

KNOWLEDGE REPRESENTATION SYSTEM. For maximal flexibility in a generative system, the knowledge domain needs to be represented. The work cited earlier shows much promise for portions of our domain. Factual information which may be in the curriculum, such as shown in Figure 21 could be represented easily enough in a semantic network. The representaion of factual information would be only a part

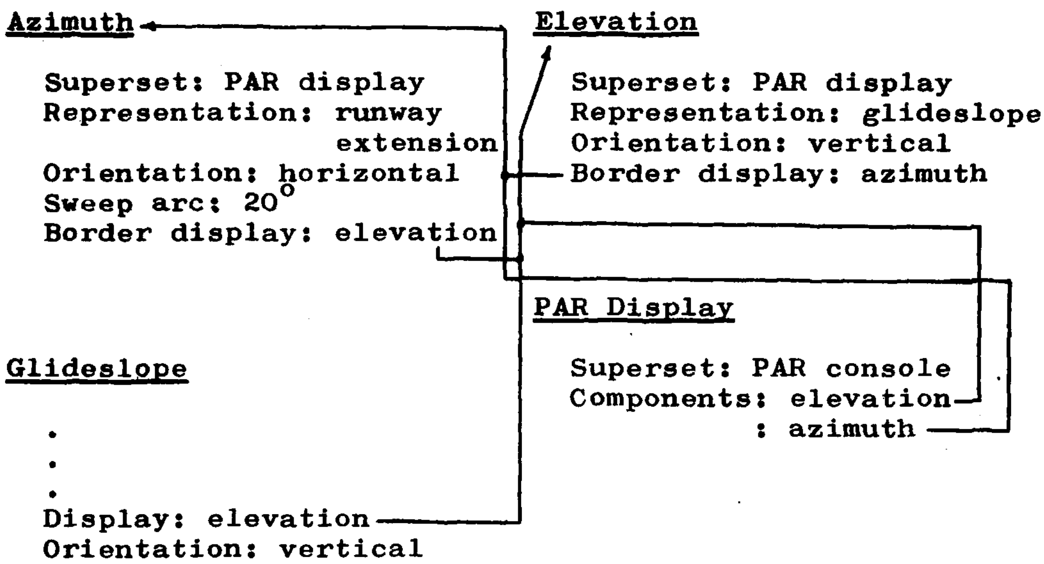

Figure 21. Illustration of the PAR Schemata as They Might be Represented in a Semantic Network

of the need however. Highly formalized procedural information (such as a "check-in" procedure), and the procedures requiring some initiative on the part of the student, (such as required of the AIC's decision as to what information the pilot needs before he intercepts the bogey) could best be represented in a genetic graph. This would allow the evolutionary stages of the student's grasp of the procedure or role to be represented. Trend calls regarding the azimuth could be represented as analogies of the trend calls on the elevation. Position calls are static forms of trend calls. The more complex procedural concepts of the AIC could be represented in their various levels of maturity.

The KRS developments cited earlier indicate that the representation of factual and procedural information is not only feasible but desireable. The research on competition for central resources however, points out an important need. The adaptive logic, as will be discussed below, of an automated-speech based training system will need to be involved in resource budgeting during the training of complex concurrent tasks. Previously we had spoken of three relationships between pairs of tasks: symbiotic, competitive, and independent. Let us assume a simple network of tasks which represent those relationships as shown in Figure 22. Let us further assume for illustration that we could quantify task demand for central resources as a percentage figure, both for tasks executed in isolation and concurrently.

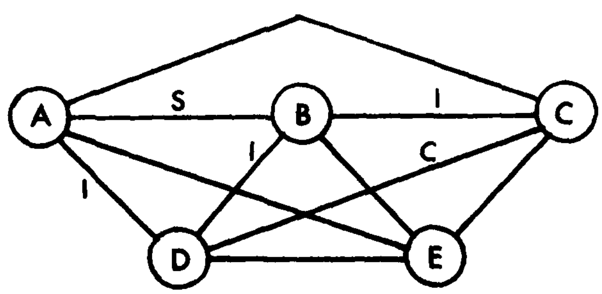

Figure 22. Network of Five Tasks with the Links Representing Symbiotic (S), Competitive (C) or Independent (I) Pairwise Relationships

As can be seen in Figure 22, tasks b and c could be introduced as two independent tasks. In isolation, let us assume that for a given level of performance on each task b and c require 50% and 70% of the resources respectively. If truly independent, then foreseeably the two tasks could be executed concurrently with no more than 70% of the central resources required. Increasing the investment of resources would increase the performance levels of both tasks. Tasks A and B are said to have a symbiotic relationship. If each required 50% in isolation, a symbiotic relationship implies that they might require only 30% concurrently. As an example trend calls might augment position calls and vice versa. Thus saying "below glidepath" followed by the trend statement "coming up" sets up an expectation for the next position call to be "slightly below glidepath." Thus trend calls and position calls could augment each other to the extent that the central resources demanded for their joint requirement could even be less than their separate demands singly.

Tasks D and C are said to have a competitive relationship. If both demand 70% of the available resources separately, then their competitive relationship would imply that their joint performance might demand more than the simple sum of their separate demands--160%. Since the student can give only 100% in total, one or the other or both of the two tasks must suffer with the student in this overload situation. In this situation, if a student were to vary his allocation of resources invested in D and C between the extremes of a 70%/30% to 30%/70% split, a POC of the type shown in the left panel of Figure 5, would be produced.

The adaptive logic of the instructor model could do one of three things at this point. First, the student could be trained in isolation on task C until it reaches automaticity or becomes more resource efficient as is shown in Figure 8. Then when 10% of the resources in isolation produce the same required level of performance as before, task D could be introduced. Again because of their competitive relation, their cost for concurrence may be more than the sum of their separate costs, say 90% > 70% + 10%. But because of the advance training on C, the joint demand of the two tasks is now manageable.

A second possibility for the adaptive logic of the instructor model would be to reduce the joint demand of the two tasks. This could be done by adjusting the adaptive variables on one or both of the tasks (e.g. the pace could be slowed by adjusting the airspeed of the approaching aircraft). This would be a more likely instructional strategy to take if the training of tasks in isolation presents a real compromise in simulation fidelity.

It may be that both previous approaches represent undesireable compromises, and that the overload situation simply cannot be avoided. The joint performance will simply have to suffer until practice eventually makes the tasks more resource efficient. In that case, the adaptive logic takes on the duties of resource budgeting. By telling the student to attend to, or concentrate on, one task more than the other, the system is manipulating the student's subjective performance utilities, and thus the indifference curves. Assuming resource allocation acquisition functions of the sort shown in Figure 12, telling the student to concentrate more on a particular task would increase the rate in which that task would be mastered (become resource efficient). As discussed previously, the job of the instructor model would be to solve for the optimal allocation of resources (the "turnpike solution") during the joint training of C and D.

In order for the instructor model to have the capabilities just described, the pairwise relationships regarding resource requirements between tasks would need to be represented. Further the representation of those relationships would need to be modified throughout the course of training. The periodic estimation of pairwise relationships would be no small feat and will be discussed with performance measurement issues.

ADAPTIVE LOGIC. As first described by Kelly (1969)[154] adaptive training has been used in various trainers, described in numerous reports, and thus will not be reviewed here (see Atkinson, 1976[155]). Briefly the idea is that performance during training can be held constant by varying an adaptive variable (presumably increasing the difficulty of the task as learning progresses.) In the present situation with multiple concurrent tasks, the adaptive logic problem is a bit more complicated. It will be recalled that Navon and Gopher (1979)[29] make a distinction between task demand and task difficulty. It will be in this sense that we will be using task demand as a potential adaptive variable.

The usage of the semantic network in generative CAI format as described above, has as its goal the building of knowledge structure. Using the terminology of Norman (1978),[73] information is provided and manipulated in the accretion and restructuring phases of learning. Adaptive training, on the contrary, is used not for the building of structures but rather for refinement or tuning of process. Once the student "knows" what it is he is supposed to do, he must practice the procedure until it becomes resource efficient or automatic. The building of knowledge structures or schemata we will refer to as the tutorial function of the system, while the tuning and extensive practice will be referred to as the adaptive function of the system.

The goal of the adaptive function is the unitizing of a structure so that it becomes automatic, or resource efficient as shown in Figure 8. At first the demands of the task (or an aggregation of tasks as discussed in the previous section) are reduced so that the student is not overloaded. As the resource efficiency increases, the task demands are increased. When the task demands reach their prescribed level, a new task may be added to the aggregate, and the demands reduced again.

The demands of the tasks can be controlled in several ways. The presentation rate of events is an obvious first choice for an adaptive variable. The speed of the approaching aircraft can be presented unrealistically slow at first so that each schema, whether it be conceptual or motoric, can be processed to completion. If task demands are too high, the student will experience many trials in which a sequence is not completed. As discussed in previous sections, it is important for the unitizing process that processing sequences be highly practiced in their entirety. The speed of the aircraft could be increased eventually beyond even the fastest normal approach rate in order to force the student into automatic processing. Just how far to go with this should be under the control of the intelligence of the system.

A second choice for an adaptive variable would be the <u>synchrony of events</u>. Since the beginning student is characterized by resource consuming controlled processing, which is serial in nature, it would be obvious that successive presentation of events rather than simultaneous presentation of events would ease his burden. In the PAR task, the aircraft would deviate only from the glidepath while staying well within tolerance on the azimuth and vice versa. Deviations would commence only after the completion of hand-off procedures. On the AIC task, the introduction of a bogey is timed to occur only after the check-in procedure has had time to be completed. Jinks occur when nothing else is demanding the subject's resources. Later in the training of the current aggregation of skills, scenarios are generated by the system in which everything seems to happen at once, or at least in close temporal proximity. Thus the synchrony of events in the generated scenarios would be controlled by the adaptive logic. When the aggregate tasks are mastered, new requirements are introduced and the adaptive logic begins generating scenarios with successive tasks again. In order for the system to possess the intelligence to generate scenarios with appropriate synchrony, some index of the current resource demands of the event are required. The estimation problem will be discussed later.

A third adaptive variable for consideration would be <u>task scheduling</u>. The system may alternate between tutorial and adaptive training modes. The tutorial mode may be entered as a new task is added to the composite, followed by an adaptive training period in which the new task is practiced in conjunction with the others already established. The adaptive feature comes in the choice of task (sequencing) and the timing of the introduction of the task. The choice of task would be based on the representation of concurrence properties (symbiotic, competitive or independent) with the previously established tasks as discussed in the last section. The choice of when to introduce the next task should be controlled by an optimizing routine such as introduced by Chant and Atkinson (1973).[36] If the new task is introduced too early, the last task may not be resource efficient enough yet, and the student would end up in an overload situation, precluding rapid acquisition of the new skill. If the task is introduced too late, the new skill may be acquired rapidly enough but time was wasted by it not being introduced earlier when the previous task became resource efficient.

NATURAL LANGUAGE CAPABILITIES. In observing students on the PAR trainer, it was observed that they had a tendency to want to turn to their human instructor and ask for help or advice, or even to comment that things were getting confusing. This desire is quite natural, and is evident in the frustration produced by nonarticulate systems wherein the student cannot take any initiative. On some systems, such as the present nonautomated PAR trainer, the real time scenario may be frozen long enough for tutorial intervention by the human instructor. This would be a desireable feature on an automated system as well. The approach of an aircraft could be frozen long enough for the student to query the system as to what he should do in the current situation. The system could also intervene when its diagnostics indicated that errors in performance were caused by structural problems rather than resource limitations. Upon entering the tutorial mode, its natural language capabilities could query the studentin further diagnosing his misconceptions. Following the tutorial intervention, the adaptive training function could be resumed.

A second function of the natural language capabilities would be to provide an articulate interface with a human supervisor in charge of training. The supervisor could query the system regarding the current status of a certain student. He could ask for the misconceptions of the student or the current status of the resource efficiency of certain task requirements. The supervisor or author of the system, during possible debugging sessions, could query the system as to why a particular task was selected at some specific point in training. The system could respond in a natural language form suitable for a training supervisor not familiar with the usual form of computer output. Wescourt et al. (1977)[145] discuss articulate interfaces along with interactive debugging aids and their potential.

DIAGNOSTICS. The complete system would be organized around a syllabus. It would intermittently alternate between its tutorial and adaptive functions either as prescribed by the syllabus, or as demanded by the dynamics of the student system interaction. Following introductory material, the syllabus might begin with tutorials in perceptual learning. Pairs of "snapshot" type images could be displayed on the CRT such as would be desireable in the training of perceptual discriminations required of the LSO. The perceptual training could be followed by tutorials required for the building of knowledge structures and procedural schemata. Interspersed in these tutorials, would be the adaptive sessions designed to fine tune each of the procedural schemata to some extent before the next tutorial. As the student advances, his progress is monitored by the updating of a student model. The updates on the student model require a constant diagnostic activity on the part of the system.

The appropriate form of remediation is inexplicably tied to the diagnosis of the cause of performance failures. The intelligence of the system must first be able to distinguish between errors of structure and process. The error may have been caused by resource limitations ("Too many things happened at once!" is the comment from the students) or the error may have been caused by a misconception (the student wouldn't have gotten the correct response even if he had unlimited time to respond). As discussed in an earlier section, errors of the first type imply adjustments in the adaptive variable(s) whereas errors of the second type imply the need for tutorial intervention to restructure schemata. In order to distinguish between structure and process errors, the task demands or scenarios may be adjusted for diagnostic purposes. If a student had given an improper heading, the system could generate the next scenario with characteristics similar to the one in which the heading error had occurred, but with a slower pace or with the critical events presented successively rather than simultaneously. In other words, adjustments in the adaptive variables, designed to reduce the demands of the task, would be implemented. If the error persists, then tutorial intervention would be required, otherwise the error would be judged as process-limitation precipitated requiring additional adjustments of the adaptive functions.

The diagnostics of the system should also be capable of discriminating between causes of errors relative to processing stages. Consider as an example the situation wherein an LSO gives the incorrect advisory, "A little more power" when in fact the pitch angle is too high and the aircraft is already slightly above glideslope. The correct advisory may have been to bring the nose down which would result in a slight increase in airspeed and a settling down on the glidepath. The incorrect advisory may have been due to the student's inability to perceive and distinguish between the fine gradations of pitch angle as shown in Figure 13 (implying deficient perceptual schemata) or if the student was process limited at the time, he may not have had time to visually scan the silhouette for its subtle features (implying that the perceptual schema has not yet been sufficiently unitized). On the other hand, the pitch may have been perceived correctly but the student has not yet established the correct cause and effect relationship between "more power" and the specific pitch angle present (implying deficiencies in conceptual schemata). Other causes could also be present such as incorrect expectancies due to his lack of experience. The point is that the different causes (perceptual, attentional, conceptual, etc.) will require different forms of remediation: additional perceptual differentiation training, tutorials on the joint effect of power and pitch, etc.

This quality of remediation requires an intelligent diagnostic componant capable of manipulating task demand parameters to this end. An additional means of diagnosis would be self-diagnosis by the student whereupon the system uses its natural language capabilities to interrogate the student. For a system without natural language capabilities, a menu of common complaints (e.g. "didn't expect it to...," "too many things happening," "didn't know what to do," etc.) could be displayed. With an appropriate choice of items, a student could adequately introspect sufficiently for realistic diagnostic purposes.

STUDENT MODEL. All the examples of CAI systems described previously have some method for representing the student in his progress through the course. It will be recalled that one form of this representation is to view the student as a growing subset of skills or knowledge units. The system keeps a record of which skills have been mastered and which are left to be acquired. In its simplest form then, each skill or knowledge structure can occupy one of only two states: learned or unlearned. A more extensive representation is illustrated by the BIP II system. It will be recalled that in this system the individual skills were viewed as occupying one of five states ranging from "unseen" to "learned." Thus acquisition was seen as a multi-state process wherein instructional strategy was dependent upon state occupancy.

Goldstein (1979)[147] in his genetic graph, provided a different technique for representing the progress of a skill. Instead of representing the skill at a single location in the network wherein the skill occupied one of two or one of five learning states, he represented the skill at several locations in the graph wherein the various locations represented evolutionary stages. His reasoning was that it is not really the same skill at those various locations but rather qualitatively different and increasingly refined versions of the skill.

What we would require in our ideal system is possibly both forms of representation: first, a single location multi-learning state representation for structural units that do not undergo change as they are learned (see Atkinson, 1976[155]) and secondly, a multi-location representation, such as in the genetic graph, when the skill or structural unit undergoes some transformation or refinement as learning progresses. We would also desire thirdly, a continuous representation of the strength of a skill or schema. This last requirement would yield information regarding the degree of automaticity of a skill which should be represented. Finally, we would also desire, to the extent possible, that the representation of the progress of a structural unit be formalized in stochastic form, which would allow the adaptive logic in the system to optimize its instructional decisions (see Chatfield and Gidcumb, 1977[37]).

PERFORMANCE MEASUREMENT. In the preceding discussions, it is apparent that performance measurement is needed for both the adaptive and tutorial functions. The adaptive logic requires performance measurement for the real time adjustment of task demand, task scheduling and event synchrony in the generation of scenarios. The tutorial function obviously needs learning state information regarding the structures in the network for the selection of tutorial strategies and dialogues. The system could not present concept B as an analogy or extension of concept A if concept A is in a primative or unlearned state.

Task scheduling requires that the system possess information regarding the resource efficiency of a task or schema and its resource sharing relations with other tasks as shown in Figure 22. Ideally we would like to record the changes in the POC for each pair of tasks, and a resource allocation function for each task. Further we would like to record the changes in the POC and resource allocation functions (see Figure 8) as training progresses. We can conclude from the outset however, that attaining and revising that much information would be an impossible task for any performance measurement technique, even if the measurements were possible. Thus the POCs between pairs of tasks may have to be approximated by discrete states (competition, independence, and symbiosis).

Crude measures or inferences of selected points in the resource allocation functions for tasks might be possible, however. To do this, some variations on the secondary task and/or probe RT methodology could be used. As an example, consider the case where the student has just mastered the time-sharing of tasks A, B, and C. We know that the "A, B, C" composite is now resource efficient because an artificial signal cancellation task (artificial in terms of it having no value in subsequent job-related duties) was added to the display simply for measurement purposes. Whenever the signal is presented, the student must immediately cancel it by pushing a button. The reaction time required for such a response could be a sensitive measure of processing load, even more so than accuracy measures (see Hunt, Lansman and Wright, 1979[19]). When the RTs are sufficiently short for the maximum demand on the "A, B, C" composite, the fourth task (D) would be added and the task demand for the new "A, B, C, D" composite reduced. If the RTs lengthen beyond tolerance limits, the demands would be decreased further. Thus the signal-cancellation measure, contrived simply for measurement purposes, could act as the performance measurement required in the adaptive logic.

If an artificial task such as the one just described is unacceptable, then adaptations to the secondary task methodology could be devised. As task D is added to the A, B, C composite, some decrement to the performance of A, B, or C or some combination thereof should be realized. The exact source of the decrement would depend on the student's subjective indifference functions. Examples of these measures would be such things as the degradation of speech quality, response latencies to events such as the jinking of a bogey, and the accuracy of computed headings. Two problems arise with these "natural" measures. The first is the discontinuity or irregularity in their occurrence and occasions for measurement. The second is that certain of the accuracy and speech degradation measures may be hard to quantify in a way which would be sensitive enough for adaptive control. Assuming that with some amount of research and development effort appropriate measures can be defined, resource demands for a given performance level and resource efficiency could be measured at some points in the resource allocation function, albeit the measurement may be indirect.

Some of the more conceptual forms of schemata or even perceptual schemata may not be directly associated with any continuous performance measurement. A PAR student may have a misconception of the details and implications of an aircraft making an approach with hydrolic system failure. This misconception cannot be continuously measured and can only be measured upon an error. Even then the diagnostics of the system must be able to identify the error as being due to the misconception rather than excessive processing demands. This is where the natural language capabilities and the intelligence of the system can be beneficial. The nonobservability of learning states has been a problem for psychologists for some time (see Greeno, 1968;[156] Greeno and Steiner, 1968;[157] Levine and Burke, 1972[158]). The problem lies in the reliance on inferences since by definition the transitions between states cannot be observed. An intelligent system may not only manipulate events for diagnostic purposes but also enter the tutorial mode and query the student. This would be a tremendous help when parameter estimation and unidentifiable states are a problem in the student model.

SELF MODIFICATION PROPERTIES. As the instructor model obtains additional data from the students, it should be able to benefit from that experience and become a more efficient training system. Examples of such benefits are discussed by Atkinson and Paulson (1972),[159] Atkinson (1976),[155] and Chant and Atkinson (1978).[160] The improvements in these examples cited, come mainly through increased precision in parameter estimation for the student models. One benefit comes from the increase in precision in the optimization algorithms, which are dependent upon the parameter estimates. A second benefit comes from qualitative changes in the student model based on the additional data. As an example, Atkinson and Paulson (1972)[159] report using the Random Trials Increments (RTI) model (Norman, (1964)[161] as the model of the student. As is characteristic of the RTI model, variation in the parameter can change its qualitative nature from that of an all-or-none process to an incremental process as extremes. By letting the parameters be estimated empirically, the most representative mix of these two models can be found. Further the representation improves with added data from additional students. This principle of self-adjustment through empirically derived estimates controlling a process, could be generalized to portions of the system other than just the student model.

SECTION V

SYSTEM DEVELOPMENT

The characteristics of the instructor model just outlined, were developed without regard to any practical limitations in terms of time and resources. These characteristics represent the ideal prototype in terms of technologies available or anticipated. Consider for a moment the position of the applied contractor who must develop a complete training system of the type just described. The sections to follow represent ventures into the world of reality with which the contractor must deal: a commentary on the practicality of implementing the ideas we have gleaned from the products of basic research.

CONTRACTING CONSIDERATIONS

For research and development (R&D) in the areas previously described, the Navy uses five levels of contracting designations. These represent levels of effort ranging from basic research to operational implementation. Simply put, these levels represent R&D stages through which a voice-interactive training system would pass in going from the idea stage to implementation and production. The various levels also represent sources of funds, and the regulation of the kinds of R&D activities that are to take place at each stage. The R&D levels defined by the Defense Acquisition Regulations (DAR), formerly the Armed Service Procurement Regulations (ASPR), are as follows: 6.1 level--research; 6.2 level--

exploratory development; 6.3 level--advanced development; 6.4 level--engineering development; and finally the last stage of operational implementation where the system goes into production and is placed into the fleet.

Funds for the 6.1 level of effort would be invested in basic research projects which would produce a technology (such as the research developments in the representation of knowledge) which might be applicable to a broad range of applied development efforts. The 6.2 designation is designed to provide funds for exploratory and feasibility studies. As an example of such an effort, Feuge et al. (1974)[2] produced a feasibility study for the PAR trainer, GCA-CTS. In this effort, he explored the functional requirements of a PAR controller, outlined a laboratory training system, and did the initial evaluation of its potential. Similar efforts have been carried out by private contractors for the feasibility and design of an auto-adaptive LSO training system (Hooks, et al. 1978[5]) and a demonstration training system for the AIC.

The contract for the development (6.4 level) of the GCA-CTS was awarded to Logicon, Inc., a private contractor. In this effort, the initial design by Breaux and others was further developed and tested. Once the system was fully developed, enhanced and tested, it was taken to a PAR training location in Memphis, Tennesee for refinement in an operational environment before going into production. An example of this development process is shown in Figure 23. As can be seen, development efforts from the 6.2 level downward are organized around a product, i.e., a training system. Only at the 6.1 level does the thematic units

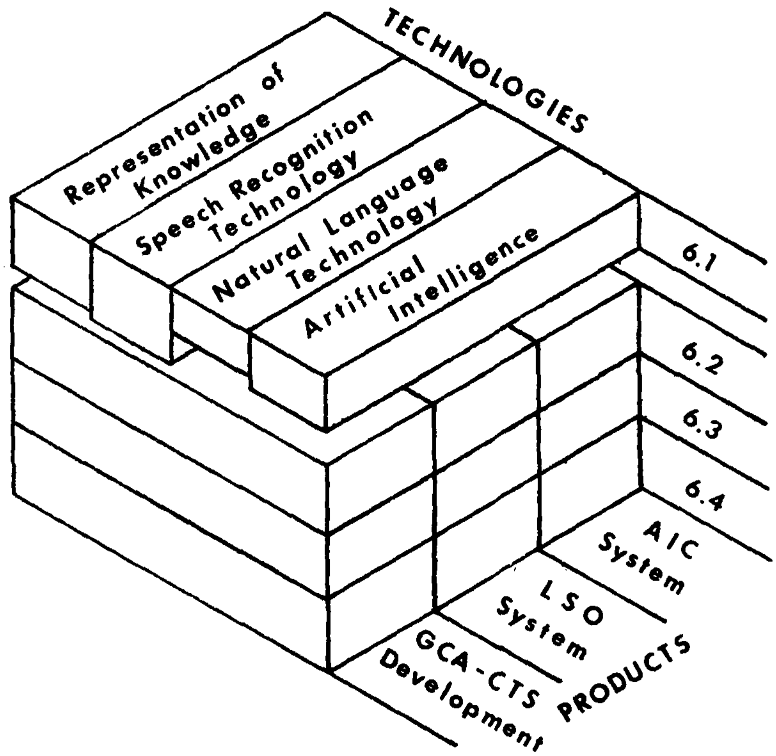

Figure 23. Present Organizational Structure of R&D Effort

cross the specific training system efforts. Thus, as an example, when the GCA-CTS was originated, it made use of the developing technology in computerized speech recognition. The research efforts in speech recognition however, transcend a single training system and can be applied to a broad spectrum of systems.

ONR is in the business of supporting basic research at the 6.1 level, although it does have some 6.2 monies. The Naval Training Equipment Center is primarily engaged in the development of training equipment at the 6.2 through the 6.4 levels, although it does have some access to 6.1 monies. The idea behind this organization is that the basic research, as described in the previous sections, is to be used by the

6.2 level contractors in developing their products. However, as is depicted in Figure 23, we propose that there is at some times a gap between the 6.1 and 6.2 and the 6.4 and production levels. There is usually continuity in personnel and contractors working on the development of a training system from the 6.2 to 6.4 levels: but because of the difference between the nature of the 6.1 and 6.2 levels of effort, there is no continuity between the respective contractors. The result is that the 6.2 level contractors are often not aware of 6.1 achievements, and the 6.1 level contractors are not aware of the 6.2 needs.

TECHNOLOGY GAPS

When a bid is solicited from contractors, the government is interested in firms that not only have sufficient physical plant facilities and capital to carry out the contract, but who also possess the personnel with the expertise to build a system which incorporates the latest of technologies. The contract however usually does not allow for much time or resources on the part of the contractor to "figure out" (6.1 effort) how to build the system (i.e. do literature searches or carry out 6.1 or 6.2 level R&D). Thus, with the constraints of time and resources, the contractor is limited to incorporating only those technologies relatively well developed which require minimal resources to apply.

The products of basic research described in the previous section are in various developmental stages relative to implementation in a system such as our ideal prototype. The most remote stage in terms of implementation would be the case wherein the technology has just been identified as being a <u>need</u>. The need may have only recently arisen and been identified as a result of a contemporary development. One step closer to implementation would be the situation wherein the technological gap or need as been partially filled by theory. Here basic theory has been formulated which describes a potential solution for the identified need, but an actual working demonstration (such as implementation in a CAI package) has not been developed. A step closer yet, would be the case that the solution has been refined and developed sufficiently to have been incorporated into a working demonstration system. The last stage, representing a minimum gap, would be the case wherein the solution or technology is in the implementation stage. Here the technology has been incorporated into a system of sufficient similarity to the system being developed that only minor modification and development would be required. This situation would be likely to arise when a firm has previously developed similar systems. These four stages of need, theory, demonstration, and implementation are, of course, not discrete. Additionally, various components of technologies may concurrently be in different stages. Still, these stages should aid us in reviewing the status of the technologies identified as desirable for an automated instructor model.

KNOWLEDGE REPRESENTATION. Semantic networks and the genetic graph are both in the demonstration stage. Though the technology exists, considerable effort would be required for implementation. An idea of the extent of the required effort can be obtained by looking at the demonstration efforts. As an example, Wescourt et al. (1977)[145] describes the development of both BIP-I and BIP-II. BIP-I was essentially developed from the theory stage and could represent a crude upper limit on development effort. BIP-II could be considered a lower limit in that second effort would have presumably benefitted from the experience on the first. The two versions would have shared the same knowledge domain as well as much of the same technical staff. Had a knowledge representation system been developed for the GCA-CTS (however most of the demonstration projects cited were still under development at the inception of GCA-CTS) the trainer would have taken longer to develop and been more costly. However, later systems such as those under development for the LSOs and AICs would have benefitted from the prior experience.

The development of a system which would represent task concurrence properties could be described as being back at the "need" stage or the beginning. The implications of this type of representation emanate from the studies cited and this report. The development of this technology would require a 6.1 level of effort, as it is doubtful that it could be incorporated into a developing system. We would propose that the development of this kind of a representation system, wherein the effects of task concurrence and developing resource efficiency is represented, begin with simulation runs. This approach would accelerate the development of the adaptive logic algorithms which would use this information as well as provide an evaluation of different forms of representation. Wescourt et al. (1977)[145] discuss their usage of simulation to test the sufficiency of BIP, but we would advocate using it earlier in the step-by-step development of the logic.

NATURAL LANGUAGE INTERFACE. The use of an articulate interface for tutorial intervention, allowing the student to initiate tutorial dialogue, and the use of natural language capabilities to assist a human instructor or supervisor, would be an extremely powerful development for the future.

This development is now at the demonstration stage, but there are some constraints in terms of its near future implementation in the instructor model. Sources at the Xerox foundation and Bolt Beranek and Newman, Inc., where its development has taken place, indicate that it presently requires a large system, e.g. PDP-10X, which would be too large to be cost-effective for the type of training systems which have been discussed. Developments in this area should be monitored, however, because of their potential.

ADAPTIVE LOGIC AND PERFORMANCE MEASUREMENT. The use of adaptive logic and performance measurement in one sense could be said to be in the implementation stage in that previous systems with a high degree of similarity have utilized these principles. However, some of the ideas expressed in this paper would require some development and could be said to be in the "need" stage. The first problem would be performance measurement. Measures more sensitive than simple error frequency would be needed for resource-efficiency estimation. This in fact could be explored to some extent by the firms developing the system. The usage of ancillary measures such as digit cancellation, and dual task latency measures in conjunction with the requisite adaptive logic in event rate, task synchrony, and task scheduling should be developed. This would require a series of 6.2 or 6.1 efforts which are not tied by a specific training system end product.

A portion of the task of building an adaptive logic and measurement system based on a resource competition model would be considered as basic research, and thus funded at the 6.1 level. The remainder of these concepts--development specifically for controller training systems--would be too specific for 6.1 funding possibly and should be carried out at the 6.2 level, perhaps by a human factors laboratory. Firms engaged in the development of a particular system would then be able to pick up the technology in a ready-to-go state.

STUDENT MODEL AND DIAGNOSTICS. The model of the student and the requisite diagnostics need to be developed in conjunction with a knowledge representation system. The current representation of the student as a growing subset of the knowledge domain is a technology in the demonstration stage. The additional representation of the acquisition or building of knowledge structures as a multi-state process is also at the demonstration stage. Thus in the current development of a training system, the designers would only need to look at the development of previous systems such as BIP. This development would probably be best done by contractors that would later be building similar systems, so as to amortize the cost of the initial development in modifying the techniques of one of the prior demonstration projects.

The formalization of the student model as a stochastic process would be another technology at the demonstration stage as are the optimization routines. The creation of a model which would represent resource efficiency however, would be best described as being in the theory stage. There are numerous strength models which could be utilized but considerable effort would be required to develop such a model. The effort would be one of those that could be either 6.1 or 6.2 efforts depending on the generality of the technology. The required effort would probably be too extensive to be included in a system development contract.

SELF-MODIFICATION PROPERTIES. The technology behind self-modification could be very important to the development of future systems. The technology is only beginning and would be considered to be in the theory stage. However, this is one of those areas that could be supported as general 6.1 research as a part of the intelligence domain, supported as 6.2 level research for specific techniques that could be conducted by human factors laboratories, or could be a part of a systems development firms own R&D program. This would be one case where it might be cost-effective for a firm to do its own R&D in that this technology could supplement a lack of technology in other areas. As an example, if a firm were awarded a contract for a training system in an area where even the SMEs may have little insight into the cognitive requirements of the task, the development of a flexible and intelligent system with self-modification properties could eventually converge on a set of rational if not optimal algorithms in instructional policy.

MOTOR THEORY. A major focus of the two current motor theories enjoying some degree of attention is the error detection mechanism. Combining some of Adam's recent discussions on new directions in KR research it would be beneficial to the understanding of the acquisition of the error detection mechanism to investigate the facilitation of error detection (and correction) as a function of the locus of KR during training trials. To the extent that error detection and correction may be considered independent processes, one could further investigate their independent development as a function of KR location.

The HPM as presented by Marteniuk and as reviewed here, makes a major distinction between open and closed tasks. In some of the preceding discussion, it was pointed out that nomenclature is too restrictive to be applied accurately to all of the component tasks of the trainer. It would therefore be worthwhile to pursue the development of a taxonomic system more versatile than the dichotomous "open vs. closed" nomenclature which is currently in use. Most probably there would be several useful dimensions of descriptors that would better reflect the processing and output characteristics of the task, as well as the input characteristics as is currently done. A better defined task (problem) would then lead, hopefully, to a more accurate solution.

EXPECTATION AND AUTOMATICITY. As discussed previously, there was some question as to the degree to which expectations, automaticity, or both were responsible for the expert's seeming resource efficiency. This would be important as instructional strategy would be dependent upon the distinction. Paradigm techniques for the investigation of this problem were suggested earlier. One other question along similar lines, would be the conditions under which the training of automaticity and expectations can be facilitated. Shiffrin and Schneider speak to this problem when they refer to consistent mapping and varied mapping conditions, category effects, etc. So basic research has produced some answers but specific recommendations within the present context need to be made. These questions, regarding the specificity for the development of the current training systems, are best placed in the 6.2 research domain. They concern the question of the training of time-shared tasks in general and would probably be more appropriate for the human factors laboratory rather than the R&D within a systems development firm.

PERCEPTION. Obviously, a big factor in the development of a training system for LSOs is going to be the development of a technique for identifying the visual features to which the LSO attends. This has already been done to some extent and is presently incorporated in the LSO training program. Additionally the technology for the training of perceptual skills needs to be established. These technologies would all be considered to be at the theoretical stage of development. Most of these efforts could be funded at either the 6.1 or 6.2 level. The AFOSR is currently funding the development of feature identification techniques as mentioned previously. The technology of perceptual training such as differentiation training, affordance training, etc. can be obtained from the basic literature but needs to be directed to the issues inherent in the automated training of controllers (probably a 6.2 level of effort). The specific identification of LSO perceptual features would have to be carried out as one of the initial efforts in the design of the training system.

INFORMATION CROSSFEED

PROBLEM. As in most technical and scientific disciplines there is a communication problem in terms of the dissemination of large amounts of technical and scientific information. The effect is that the applied scientists developing the training systems are not able to incorporate recent advances from basic research, while the basic researchers are not aware of the applied needs. This problem is acute in that a good portion of the basic research reviewed in the present report is funded by the Navy (ONR) while the current needs discussed herein also emanate from the Navy (NAVTRAEQUIPCEN). As a part of the contract which produced this report, the senior author was able to attend meetings regarding this problem as well as to discuss possible solutions with personnel from both the applied and basic domain. From these discussions it was concluded that the overall problem was two-fold. One was an "awareness" problem and the other was the "state-of-the-technology."

AWARENESS. It is of course difficult to describe the characteristics of a group of individuals such as applied scientists in that their levels of awareness in the areas reviewed in this report would vary in terms of their area of expertise and the area of their current projects. We feel it safe to say however, that most have only marginal knowledge of the current ONR programs being funded. They may know the general thrust of ONR funding but lack the awareness of the current technological products coming out. The current authors, prior to this review, were in the same state. After reviewing the programs it was evident that a major portion of the basic research which would impact automated training, is being supported by ONR. Thus, if one could even keep abreast of these programs, part of the awareness problem could be solved. For the benefit of interested readers, Appendix A includes a synopsis of the ONR programs and various projects.

The information summarizing the ONR efforts was provided by that office for this report, but the information is not routinely disseminated. It was the opinion of several scientists that it would be beneficial if information such as this were provided to the applied community. (The form of the information may need to be revised somewhat however.) More than one commented when shown a listing and synopsis of the ONR programs, that it was not readily apparent how some of the products of basic research could be applied to their projects. Thus it was suggested that, not only would regular announcements of ONR projects be helpful, but the abstracting of the projects could be organized along the lines of their impact on applied programs.

As can be seen in the present review, the literature that would impact the development of training systems, whether it be funded by ONR, AFOSR, National Science Foundation (NSF), etc., is varied and quite extensive. No one resource person is going to be able to keep abreast of all the areas of perception, cognition, CAI, motor learning, speech recognition, artificial intelligence, control theory, and systems programming. Thus a periodic review of the literature would be required of various personnel.

The question of the cost of keeping abreast of the literature must be addressed. Though it is not a major cost, it is certainly noticeable in a competitive bidding environment where the government wants an accounting of all activities. The systems development firms themselves must of course bear the cost of at least keeping abreast of the basic developments that were listed as being in the demonstration stage. But the government itself should bear some of the cost by providing dissemination channels, conferences, workshops, etc. This it already does to some extent, but the comments received were that an overview and translation of the products of basic research and their relevance would be beneficial. The present report is in part an attempt by the government, i.e. the Naval Training Equipment Center, to summarize and translate some of the achievements of basic research, in terms of its relevance to the development of automated-speech-based training systems.

STATE OF THE TECHNOLOGY. Simply reviewing and summarizing the literature is not sufficient. As noted in a previous section, the products of basic research are in various stages of completion regarding immediate implementation. Some are only in the demonstration or theory stage and are likely to remain there until an applied effort is initiated which will continue the development in the direction of the training systems. Other products may be immediately applied with only minimal modification. The point is, however, that the technological breakthroughs require some developmental effort to be applied.

Awareness is only a part of the problem. ONR could distribute summaries of projects, NAVTRAEQUIPCEN could sponsor periodic reviews of the literature, and workshops on current developments could be held, and still a good portion of the developments would not be implemented. It is our opinion that the reason lies in the nature of current contracting practices.

Informally it could be said that there are two types of contracts that are let. One could be best described as a technology oriented contract where the effort is to attempt to solve a problem by executing certain agreed upon activities. The outcome of the effort, like research in any discipline, is uncertain. The contractor, attacking the problem with great scientific skills and executing the experimental manipulation in the grandest of style cannot guarantee the direction of the data, or even that the problem will be solved. What he agrees to in the contract is to expend an agreed upon amount of resources in carrying out the general approach or design with which he won the contract award.

The second type of contract, may be referred to as product oriented. In this case, the contract requires an end product, or a solution as it were, for the efforts expended. All contracts require an end product of some kind, even if it's simply a report on what has been achieved. But in this second case we are referring to the type of contract wherein a certain milestone must be achieved. As an example, it may be that a trainer, meeting certain miminum capabilities, must be produced within the time frame and budget limits. If unforeseen technical problems arise, the extra effort required to fulfill the terms of the contract may be at the contractor's own expense.

The division of contracts into technology oriented and product oriented groupings is obviously an oversimplification but it serves a descriptive purpose. Most all the 6.1 efforts and some 6.2 efforts are of course technology oriented, while the rest of the 6.2 efforts and the remaining developmental levels are product oriented. Since development firms and research organizations have tended to specialize in terms of the type of contracts they pursue, a discontinuity in the total process as described in Figure 23 has resulted. Thus the basic researcher, who might be working on a knowledge representation system (KRS) for example, selects a subject domain within which to work, and then proceeds until his ideas are proven viable. He then leaves that particular effort to tackle other basic research problems.

In developing a training system such as the automated-speech-based systems, the product oriented contractor may be aware of the previous achievements in knowledge representation systems. But having not been a part of the basic research effort, his personnel may not have the technical experience required to efficiently implement that technology. Further, once the basic research contract had proven the viability of the KRS, it would not be rational to expect the basic researcher to explore the details of all possible applications. Thus when the KRS, though sound conceptually, is applied specifically to one of the automated-speech-based systems, problems may arise requiring unanticipated resources to resolve. Knowing this, the product oriented contractor is reluctant to attempt to implement new technologies when he is responsible for the "result" not just the "process." In fact he may be reluctant to bid on an RFP which requires implementation of a KRS because it is too open-ended. Being unfamiliar with a viable but nonspecific technology, he is unable to estimate the costs of the R&D which must precede implementation.

Awareness then is only part of the problem. The gaps between the state of the technology when it leaves the basic researcher and the state which would be required by the product oriented contractor is the other part. One solution would be for the applied contractor to engage in his own R&D effort to fill the gap so that he might stay competitive when bidding on automated-speech-based systems. This would have to be taken from the profit margin and amortized over several development efforts. This is somewhat prohibitive for most firms, however, in that the government accounting system attempts to keep the profit rate down and only allows direct development costs to be charged against a particular contract. Thus general R&D, if it can not be attributed to a specific contract, must come out of the limited profits. In interviews with personnel from the Defense Contracts Accounting Agency (DCAA), there are some exceptions to our statements, wherein contractors may claim the expenses of general R&D. Some readers may want to explore those possibilities further.

Another solution is for the government to attempt to fill the technological gaps. This could be done by a series of 6.1 or 6.2 level research oriented contracts in which the goal of the efforts is not new breakthroughs (as in the basic research efforts), but rather the extension or application of technologies already achieved in the basic domain. For example, an "application R&D" effort could be designed to extend present developments in a KRS to the knowledge domain of an AIC, wherein the further extension to PAR and LSO would require only minimal effort. An illustrative example of the efforts described is shown in Figure 24. It would be beneficial if the "application R&D" effort spanning the automated-speech-based systems, could be executed by some of the same firms that might be developing the systems at the lower levels. This would provide for a continuity in personnel. Otherwise, the efforts could be carried out by other contractors or the human factors laboratories monitoring the efforts. Care would have to be taken in that case however to ensure that the "extension" or "application" technology gets transmitted to the "product oriented" contractors down the line.

A final possible solution is to feed the information as to the needs of the automated-speech-based development back to some of the basic researchers. Often, when developing training technology, the basic researcher needs a subject domain in which to work. In fact, several have

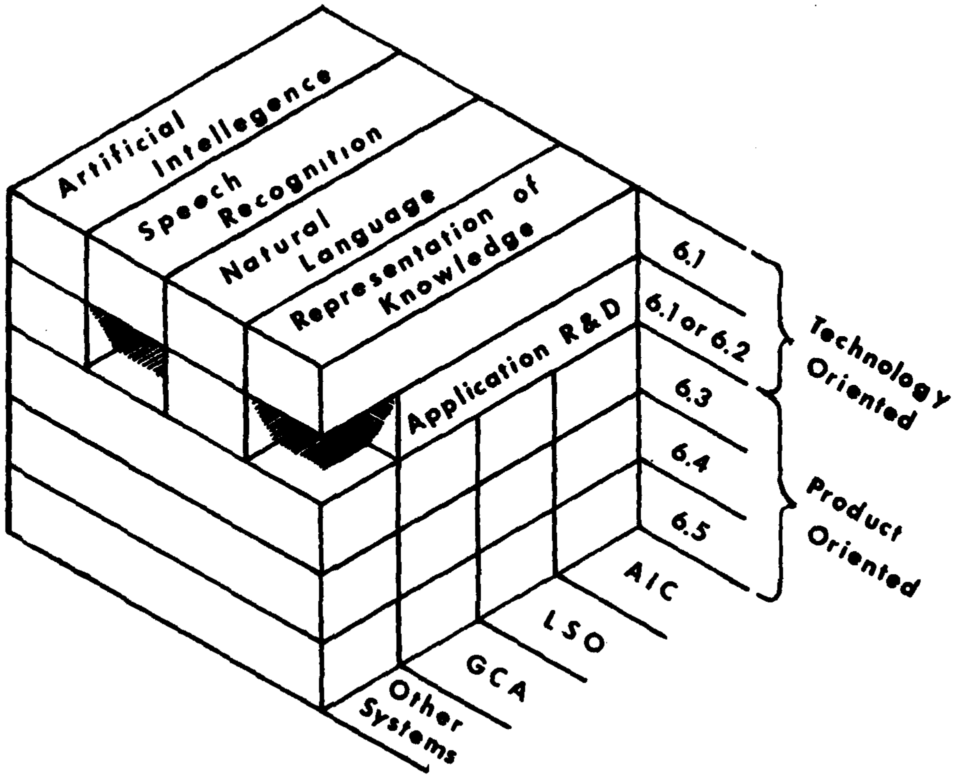

Figure 24. Proposed Organizational Structure of R&D Efforts

shown interest in the GCA-CTS. If they were to adept a GCA-CTS-like medium in which to work, little effort would subsequently be required to implement the system in a real training environment.

SOLUTIONS. Two possible solutions present themselves: (1) tackling the awareness problem by increasing the cross-feed of information between the basic researcher and the product oriented contractor; and (2) funding "application

R&D" efforts. During the month of July 1979, meetings were held with representatives from ONR, NAVTRAEQUIPCEN, and the senior author from Behavioral Evaluation & Training Systems (BETS), in which these problems were discussed. One solution proposed at these meetings was to hold two conferences, approximately a year apart. At the first conference, product oriented contractors, and representatives of the monitoring human factors laboratories would present the needs of current and future training systems, similar to the three systems described in the present report. The audience in this first conference would be a group of basic researchers. In the second meeting, the roles of speakers and audience would be reversed. The basic researchers, having been exposed to applied needs, would present their technologies and explanations as to what the gaps are estimated to be, and the kinds of efforts required for implementation. At the time of this writing, a conference is being planned.

Other possible solutions discussed were the reorganization and dissemination of summaries of ONR efforts and periodic reports generated to review basic technologies for selected applications. Additionally exploratory 6.2 level contracts could be written so as to be more research oriented rather than product oriented to allow the systems-development firms to engage in the R&D required to extend basic technologies thus increasing continuity. The firms themselves could also explore their cost accounting practices with the DCAA and other agencies to see if their own R&D could be amortized over projects.

SECTION VI

SUMMARY

This report has examined the training characteristics of the Ground Controlled Approach (GCA) radar controller, the Landing Signal Officer (LSO) and the Air Intercept Controller (AIC). The expert and novice, in respect to these three tasks were contrasted in terms of their relative skills. The novice was characterized as a controlled serial-processing system, unable to effectively perform in a concurrent task environment, wherein the tasks compete for the same pool of central resources. The expert on the other hand, was characterized as a resource efficient system capable of preprocessing and automatic responding. Several areas of basic research were reviewed in search of a set of technologies with which an instructor model, resident in an automated speech-recognition- based training system, might be designed. Research in cognitive processing limitations and components were examined in some depth along with recent developments in intelligent knowledge-based computer assisted instruction (CAI).

The result was an outline of the characteristics of a prototypic instructor model. Some of the technologies incorporated in the prototype were insufficiently developed along the lines of the three aircraft controller tasks and thus further research and development (R&D) would be required for implementation. Finally, recommendations for R&D and the dissemination of information were discussed. In short, this report represents an attempt to summarize

and translate some of the achievements of basic research into their relevance for the continuing development of automated speech-based training systems.

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APPENDIX A

DESCRIPTIONS OF RECENT CAI RELATED RESEARCH BY ONR.

The Office of Naval Research (ONR) sponsors two main areas of research in order to enable improvements or advances to be made in naval operations. The first area involves basic or fundamental research. The efforts to gain fundamental knowledge are generally of long term and are aimed at obtaining information leading to the solutions to naval problems. In the second area research efforts involve development of new technologies and the testing of new concepts for naval operations. Since the needs of naval operations span diverse fields of specialization, much of the research sponsored by ONR is interdisciplinary.

Because of the broad spectrum of factors affecting naval operations, ONR has been organized into ten specific science and technology divisions to handle the research needs of the Navy. The divisions range from the Naval Vehicles and Weapons Technology Division through the Biological Sciences Divisions and the Arctic and Earth Sciences Division to the Analysis and Support Division. Of the ten divisions, the Psychological Sciences Division is organized into 18 clusters with five of these clusters pertinent to CAI: information processing abilities, representation of knowledge, cognitive processes, visual and auditory perception, and information processing and decision making. The latter two clusters are relevant in so far as they each provide information about the basic underlying functions of human information processing. The other three clusters are more directly involved in the development of CAI.

The following information describing the clusters and the research conducted within the framework of the clusters was obtained from the fiscal year programs booklets produced by the Psychological Sciences Division. The research efforts cited here should not be considered as reviews but descriptions illustrating the research sponsored by the Psychological Sciences Division and ONR.

The first cluster to be discussed deals with information processing abilities. The purpose of research conducted in this cluster is to investigate basic information processing operations that underlie task abilities. There are three major areas of interest within the information processing abilities cluster: the implication of individual differences in the parameters of some basic information processing functions, performance in complex tasks as a function of proficiency in the basic information processing functions underlying those tasks, and the potential of information processing theories to provide substantive explanations of the relationship between mental test performance and performance in real world tasks.

The first work unit to be described is one by J.B. Carroll. The first of three proposed reports has already been completed. The report consists of two parts: a critique of correlational techniques and related statistics as applied to information processing research on individual differences, and an analysis concerning the conclusions to be drawn about traits, factors, cognitive processes, and individual differences.

In the next work unit begun in FY77, a test battery designed for use as an assessment instrument for the evaluation of performance is being developed. A.M. Rose in an initial version of the battery has included such tasks as mental comparison, memory scanning, and graphemic and phonemic classification. Some other tasks which may be included in the final battery include free recall, susceptibility to interference, and mental calculation.

R.J. Sternberg began a planned five-year effort in FY78 with the formulation and evaluation of a general theory of human reasoning components. His theory assumes deductive and inductive reasoning processes are the components under study. According to the theory, there may be some individual variation in the use or non-use of the component processes forming the mental representations upon which the processes act. In addition individuals may also vary according to the strategies employed in the blending of the processes, how consistantly those strategies are applied, and in the speed and accuracy of the component processes. Sternberg is also formulating specific mathematical models of simple reasoning tasks involving the component processes. These mathematical models could then be used in characterizing individual differences and relating the differences to standard psychometric measure of related abilities.

B. Schneider in some of his earlier work formulated a theory that classified detection tasks as either control processing or automatic processing. In control processing, tasks are accomplished by a slow, serial, capacity-limited process having a considerable cognitive load. Automatic processing, on the other hand, occurs over a fast, parallel capacity, unlimited channel with little if any cognitive load. The automatic processing becomes possible only after extensive training with a consistent stimulus-response mapping. The project funded by ONR which began during FY78 will look as the implications of Schneider's theory in individual differences and the prediction of performance.

AD-A079 902 BEHAVIORAL EVALUATION AND TRAINING SYSTEMS LUBBOCK TX F/G 5/9
INSTRUCTOR MODEL CHARACTERISTICS FOR AUTOMATED SPEECH TECHNOLOG--ETC(U)
OCT 79 D C CHATFIELD, P H MARSHALL N61339-79-C-0085
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In a one year project begun FY78, J.E. Hoffman is investigating the acquisition of automatic detection by a fast, unlimited capacity mechanism requiring little, if any cognitive effort. The output of this mechanism is described as an index of the similarity of the stimulus and target sets. Medial values of the index produce a slow, serial process, while values at either extreme permit the subject to make immediate responses. Through training a subject refines the similarity index toward the extremes. The goal of Hoffman's project is the formulation of a model allowing quantitative evaluation of the effects of individual differences during training upon the similarity index.

A research effort begun in FY77 is focusing on the hypothesis that "complex tasks draw upon a reservoir of spare capacity" which varies between individuals in its size. By measuring the performance degradation upon a concurrent secondary task, E. Hunt has been able to determine the task demands of a given primary task on the capacity reservoir. Using this measurement technique, Hunt is attempting to formulate a general method which will allow performance on complex tasks to be predicted by measuring performance requirements of the simpler component tasks. Prediction of performance in difficult problem-solving situations could be accomplished without exposing personnel to the target situation by applying the methodology being prepared by Hunt.

S.W. Keele was attempting to obtain information which would allow some resolution to the conflicts between various theories of attention, particularly as they relate to personnel selection and individualization of training. The approach taken in this three year effort, completed in FY78, involved the flexibility of attention. Individuals differ in terms of the point where they no longer incorporate items and begin to exclude items of information from attention. During the course of this project, Keele found the "fusion" phenomena (the fusing of dichotic inputs such as "lanet" and "panet" into a single word "planet") to be more a function of subjects having difficulty in determining the temporal order. He also found that individual differences in memory span are not attributable to variation of memory strategy. In a third problem area investigated by Keele, a theory of attention was developed placing capacity limits on response selection rather than stimulus analysis.

The result of a planned three year effort begun in FY78 by Keele is a test battery capable of predicting complex task performance based upon simple tasks. The project started by obtaining pure measures of five hypothesized cognitive ability factors. Concurrent validity studies of the battery will be performed once measures have been established for all the cognitive ability factors. The final phase of the project is to conduct predictive validity studies using flight-school students.

J.R. Frederiksen began a three-year effort in FY77 aimed at the identification of perceptual and cognitive skills related to reading and verbal ability. In the course of the research, techniques for measuring these skills will be formulated and the effects of skill deficiencies on reading ability will be investigated. A series of experiments have defined skill deficiencies of poor readers and five basic components of reading have been determined.

The ability to process information at the appropriate level also seems to vary across individuals. In this regard, two types of individuals have been classified: language bound and language optional. Language bound people are constrained in their thinking by the rules of their language or other high-level conceptual schemata, while language optional people are able to operate without the language constraints when the task requires this of them. R.S. Day in this three year effort begun in FY77 has found that perceptual or sensory deficits, intelligence, or other artifacts are not the source of the phenomenon. Additionally, language bound people have been found to process stimuli to deeper levels of analysis. During the final phase of the project, data was to be obtained on demographic and biographic factors.

A research project by R.E. Snow begun in FY77 was seeking to understand situations in which aptitude-treatment interaction occur. He constructed an aptitude theory which allows the abilities measured by aptitude test to be represented in terms of the information processing required by the tests. The theory goes on to relate the information processing to the interaction of instructional and differing individual aptitudes. An information processing description of the aptitude treatment interaction is possible with a theory such as this. Data indicates a two-step process is followed by individuals who are successful, high-aptitude processors. The process consists of constructing the eorrect answer and searching the response alternatives for the answer. A less systematic, parallel processing of both items and responses characterizes the less successful, low aptitude processors. Indications are that an individual's strategic flexibility may be more important in determining aptitude affecting learning than had been suspected.

E.A. Fleishman in an earlier work used factor analytic techniques to analyze job performance and suggested that 37 abilities can be used to describe that performance. Following up on this finding, Fleishman began an investigation into the general trainability of these abilities. The hypothesis is that certain procedures used in the training of specific abilities will allow a high degree of transfer to all tasks making use of those abilites. Three abilities have been chosen for training and the experimental designs developed to test for the breadth of training generalization. Validation of this training transfer concept was planned for the last year of funding.

A theory of memory developed in 1969 by B.J. Underwood which posits that memories are a collection of attributes forms the basis for a three year effort completed during FY78. Using a factor analytic technique on a variety of tasks, Underwood identified five factors. These factors however related more to the form of the stimuli and task requirements than to memory attributes. This finding was of substantial theoretical interest since all tasks studied relied heavily on associative processes leading to an interpretation that associative processes may be multidimensional. The results from another thrust of the work suggest that simultaneous as opposed to successive learning of tasks enhances long term retention.

Observing that most studies of human memory involve a single task while real-world training requires an individual to learn a variety of tasks and switch among them on an irregular basis, Underwood began a new research effort in FY78 to investigate learning in multiple task situations. The main concern is the determination of the generalizability of known laws of human memory to a situation where individuals must learn multiple tasks simultaneously.

Given the marginal reading skills of new recruits entering the service, an effort to determine the most efficient remedial program would seem appropriate. Carver, in a work unit completed in FY78, attempted to relate reasoning ability to reading proficiency. A positive relationship would indicate those individuals having good reasoning ability would gain the most from a remedial reading program. However, the testing of students previously divided according to high and low scores on a test of reasoning ability, following extensive reading tutorials administered by computer, indicated no significant differences between groups.

The next cluster involves representing knowledge for training. The psychological foundations of computer based, interactive, adaptive instruction is the main concern of this cluster. There are two areas of emphasis in this cluster: the representation of knowledge and the process of instruction itself. Knowing how to represent knowledge is important if the computer in a CAI program is to function effectively. The computer must be able to answer natural-language questions, be able to generate examples and problems appropriate to the learning context, and evaluate the student's knowledge of the subject material being taught. Studying the process of instruction will allow the most effective strategies to be developed.

Students arriving for training have different cultural and educational backgrounds which leads to a wide variance concerning the initial knowledge of the subject matter and their motivation. A training program which is based upon network models of human memory would allow an optimum match of the instructional material to the student's abilities. D.A. Norman in a project completed in FY76 attempted to build such network models and to construct a representation of the semantic and syntactic structures of the information to be learned by the student in order to build an optimizing training program. The results of developing such a program would also lead to new understanding of human memory.

Continuing his research into semantic network representations, Norman started a new project in FY77. This project has two focal points, the investigation of basic principles of instruction and the development of operational computer based tutorial systems. These computer systems will be used as testbeds for the study of the instruction principles and as prototypes for potential application. A completely automated tutorial system which uses a semantic memory representation of the subject matter is being explored. Norman is also exploring a semi-automated tutor making use of a state-dependent teaching strategy. The theoretical work has centered on two aspects of learning: that learning is not a homogenous process and that a student's prior knowledge is critical in acquiring new information.

J.W. Rigney has been investigating theoretical and empirical bases of instruction so as to improve the effectiveness of training. The focus of the empirical investigation has been the development of a computerized hands-on maintenance training testbed and the advanced computer techniques required for such development. A computer-based General Maintenance Training System (GMTS) has been developed and field tested. Further real-world testing of the GMTS is underway. The theoretical emphasis has been the development of a general theory of computer-based instruction. Studies completed have involved: descriptions of cognitive processing in terms of schema theory, strategies used in the extracting of logical relationships from written material, electrophysiological correlates of cognitive processing, and the effect on summaries and recall of different text structures.

In a related effort begun FY77, Rigney focused on the formulation of a model to teach the self-directional processes involved in on-the-job training using technical material. This model would be used by military personnel as an aid in their own self-directed training. This would be accomplished by teaching them how to select their goals and then obtain the relevant information from the technical documents used for the self-directed training.

Traditional CAI systems are "frame oriented" and make use of "canned" questions and the answers to these questions must be one of those "canned" answers anticipated by the human instructor at the time of programming. As a result, these traditional CAI systems have limited flexibility and a restricted potential for the individualizing of instruction. A. Collins expanded an existing "mixed initiative" CAI system SCHOLAR, which is capable of generating its own questions and making appropriate responses to inputs from students. Such a system uses a self-contained hierarchically structured data base of facts, concepts, and procedures. In this research, Collins sought the improvement of the interactive capabilities of a CAI system through the development of programs and techniques allowing continuous natural-language dialogue.

In a subsequent effort started during FY77, Collins is attempting to use a generative CAI system to teach causal knowledge and reasoning. Using this system, various tutoring strategies can be tested for the relative effectiveness while holding all other variables constant, something not possible with a human tutor. Additionally, a theory of tutoring developed through analysis of tutor-student dialogues is being incorporated into the CAI system to enable the program to determine the student's current status and make a diagnosis of errors. The optimal strategy will be determined by comparing the learning levels attained by the students under different versions of the program.

J.R. Anderson is developing a computer model for the learning of skills and procedures as opposed to the learning of facts. The resulting computer programs are to be "taught" from topic areas and the output of the simulation examined for general aspects of human learning. Use of this model should enable the evaluation of the effects of various training techniques, the teaching of new training skills, and the evaluation and remediation of cognitive skills deficiencies. One of the results already obtained suggests principles of learning acquired from studies-of-fact learning may be more generalizable to the learning of procedures than expected.

A one-year effort by K.T. Wescourt completed during FY78 examined the possible improvement of students' abilities to solve troubleshooting (debugging) problems if they are given explicit instruction in general problem-solving methods rather than the students acquiring the methods through trial-and-error learning. Data analysis indicated that experienced programmers debugging expertise is the result of their idiosyncratic experience and the differences in the debugging competence of inexperienced programmers is a function of their use of general problem-solving methods. Failure to adequately diagnose a program malfunction and an inability to back up when an attempted correction failed as a cure are the characteristics frequently associated with the inefficient and unsuccessful debugging attempts of inexperienced protrammers.

P. Suppes and K.T. Wescourt completed a research effort during FY77 dealing with a generative CAI system which made use of a network representation of the course content to be taught. Individualized teaching was made possible through the use of a "curriculum driver" which developed a sequence of tasks for each student based upon the contents of the network and made reference to the current status of the student's mastery of the target skills.

Previously undiscovered conventions that regulate human dialogue were identified by W.C. Mann in a study completed during FY77. Termed "Dialogue-Games," these conventions are recurrent structures defined by the goals and subgoals of the dialogue. Mann used naturally occuring human dialogues as the source of his data. A Dialogue-Game was found to communicate a large number of non-explicit understandings. Much of the brevity, interpretive selectivity, and covert inference found in ordinary human interaction is attributable to these Dialogue-Games. It is suggested that man-machine interaction could be more concise and more flexible if these Dialogue-Games could be transferred to man-machine systems.

The last cluster of the Psychological Sciences Division to be described involves cognitive processes. This was a program initiated in FY78 to characterize skilled performance in real world tasks demanding complex information processing. The cognitive processes program emphasizes four main areas: information collection and analysis, the representation of task domains by problem solvers of varying levels of expertise, search and planning processes involved in skilled problem solving, and important features in the execution of problem solutions.

D. Kieras is studying aspects of text comprehension in an effort to discover how people determine the subject of reading material after only processing superficial features of the text and the full comprehension or knowledge of the relevant context and background has yet to be attained. This research has value in that jobs involving text comprehension generally require the reader to decide the topic or subject of the material inorder to decide relevancy of the material and obtain the overall context required for deeper concentration. Results from experiments will be used to form a computer simulation model which is to be checked against behavior data. The simulation would then be applied to describe topic identification strategies and as an aid to the training of more efficient topic identification.

W. Kintsch has developed a theory of text comprehension which allows the evaluation of a readers' proficiency in decomposing text into a set of propositions representing its meaning. These propositions become the input of a concept learning theory by L. Bourne that describes how people determine which types of information predict the value of an item or task based upon their experience. This joint effort by Bourne and Kintsch will examine the effect of different text structures on the prediction task and the parameters of the concept learning of the task.

J.G. Greeno is concerned with the relationship of the syntactic properties to the semantic properties of a domain. Choosing plane geometry as a prototypical case because the axioms and theorems contain syntactic properties and the semantic properties can be represented by diagrams and other geometric properties of construction, Greeno will attempt to formulate a theory of geometry problem solving. This theory will describe the roles and interactions of axiomatic formal reasoning and diagramatic informal reasoning. In a related theoretical work, an attempt to describe the causal structure of semantic knowledge provided by studies of rapid scanning of diagrams and other properties of diagrams in a semantic network will be made.

A five-year effort to study the differences between novice and expert problem solvers is planned by R. Glaser. This analysis will use two classes of problems, analytical and perceptual, to determine how the novices differ from the experts in their representation of the problems. The ability to produce relevant facts to particular problems and the effects of various types of priming on the appropriate representation will be studied. Also to be studied is the ability to construct and draw inferences from external representations. Later phases of the project will investigate such aspects of problem solving as planning, search, execution, and checking. Perceptual fluency will be combined with artificial intelligence approaches to spatial and locational cognition in studies of perceptual problem solving. A series of studies allowing an analysis of the patterns and procedures used by people in the interpretation of maps is also planned.

A three-year study by P. Thorndyke addresses four main issues: map learning, mental map construction, representation of geographical information, and distance estimation. The analysis of an initial study of map learning indicates individual differences may be attributable to strategic sources. From work in the area of mental map construction it was found that actual navigational experience produces more locale knowledge while map experience enhances the acquisition of global knowledge. A dual-code theory which assumes both relational and analog codes for spatial knowledge is the central theme for studies of the representational knowledge. The effect of clutter along the distance to be estimated is the concern of distance estimation studies. Clutter seems to cause overestimation of distances, apparently a phenomena unique to memorized maps.

A theory of route planning is the topic of a planned three year effort by A. Stevens. Taking the form of a "planning grammar," the theory will represent various types of route plans and describe how various types of representation of locale are used by people. A computer-based simulation will be used to empirically evaluate the theory. One of the data analysis approaches will attempt to interpret planning errors in terms of the plans or subplans which produce the errors.

A theory of human planning in the context of software design is the goal of a project headed by M. Atwood. Planned for two years, the effort will investigate the theoretical assumption that planning takes the form of a "procedural network." The internal assumption of the procedural network is that planning occurs by expanding each abstract part into more concrete subparts and by ensuring the appropriate coordination of the generated subparts. The techniques developed in the project will be used in a variety of ways, for example: the order of expansion of the networks can be determined and an examination of the ways in which design and planning knowledge are combined with planning of the tasks or problem domain can be performed.

B. Hayes-Roth plans to use an "opportunistic" theoretical approach to human planning rather than a "hierarchical" approach as used by Atwood. This theory holds that a number of parallel, independent knowledge sources accomplish the planning by communicating through a central data base which records the plan and other related material. Each of these knowledge sources is capable of specific modification of the data base whenever the required conditions are met. Hierarchical planning of the type described by Atwood is possible since some of the knowledge sources act on abstract data by expanding the data into more concrete forms. However, this form of hierarchy can flow in the reverse direction with some knowledge sources creating abstract data from the more concrete data presented as input.

The Mathematic Sciences Division of ONR (as described in the ONR Publication: Contract Research and Technology Program) also sponsors research relevant to CAI. This division has three main areas: operations research, statistics and probability, and information systems. The research programs sponsored in this last area are the ones of interest in the development of CAI. The information systems area has four program thrusts: computer hardware and device design, large file systems, software design, and man-machine symbiosis. Of these four programs, the study of man-machine symbiosis most directly applies to CAI. Four program areas comprise the man-machine symbiosis area: computer-aided design, artificial intelligence, natural language interaction, and speech understanding. Only the last three areas apply to CAI development. The following research descriptions are the result of personal communication with Gordon Goldstein, Director of Information Systems Programs.

The application of artificial intelligence (AI) to a CAI system would allow that system to become more dynamic and flexible in its interaction with students. Some of the AI research sponsored by the Mathematical Sciences Division is allowing the development of AI techniques which could be applied to CAI systems.

A work unit being conducted by C. Hewitt, involves the application of AI to the solving of large data base problems. Although aimed at problems in the logistics environment, CAI systems also will have difficulty with large files used for the storage of the accumulated knowledge needed for a dynamic, flexible CAI system.

R. Reddy is investigating the development of AI in the direction of dynamic acquisition of world knowledge by the computer and the ability of the computer to modify its behavior according to percieved changes in the external environment. In addition, work has involved the development of automatic visual learning through the combination of symbolic and signal processing information. Addition of features such as these would allow the human teacher or tutor to give the CAI system the knowledge required for teaching and to usual visually presented material in that teaching. The ability to modify its behavior according to input from the environment would aid in the CAI systems' capability to adapt to changes in student performance more readily.

A project directed by E. Charniak has as its goal the development of a computer system capable of "reading" a text and extracting enough information to allow the questions at the end of the chapter to be answered. Thus the CAI system could "learn" the contents of a course text to form the knowledge base used in the teaching of that course. Initially a program to solve the chapter problems given a preprogrammed knowledge base is being attempted. Later phases will be concerned with the acquisition of knowledge by the system.

M. Minsky is seeking to establish a theory and process of "knowledge based computer problem solving." His approach is to view an intelligent problem solver as a network or society of specialists with each specialist having a large data base applicable to its domain. These specialist computer system components are each capable of solving problems within its domain. Three possibilities are proposed for the integration of the specialists in the solving of a general problem: an expert on the specialists to distribute those portions of the problem to appropriate components, a negotiation system which will allow the specialists to operate in parallel upon those problem components having the greatest association with their expertise, and a combination of expert and negotiation systems.

One of the large barriers to widespread use of CAI systems is the inability of the system to communicate with the student in his natural language rather than a highly specialized subset of the language having very limited vocabulary. L. R. Harris and S. J. Garland are attempting to improve the natural language capabilities of computers input and control. In the same vein, D.L. Waltz is attempting to develop a language system which will selectively retrieve information from data storage, as a response to user interrogation, and respond with the answer in readable form, all in real-time. The goal of a project headed by W.A. Woods is to build an AI system capable of not only interacting in natural language but also able to make comparisons and draw analogies over narrative data or to generalize over information sources. The resulting products of these research efforts when applied to CAI systems will allow non-computer oriented personnel to interact effectively with the system. CAI systems could then become even more generalized in their usage and more flexible in their interaction with students.

Speech decoding and synthesis is another area of research which is aimed at more natural interaction with computers. J.D. Markel has been investigating the ability to use speech synthesis over telephone systems and has met with some success. Using basic research in speech analysis and synthesis techniques, J.E. Shoup is attempting to develop the means of obtaining automatic derivation of accoustical parameters for automatic recognition and synthesis. With such capabilities, the normalization of inter-speaker differences becomes more of a reality. In a real-world situation a student may seldom have access to a CAI system without also having background noise levels degrading his speech. A.V. Oppenheim has been working toward a solution to such a problem by developing enhancement techniques for degraded speech. Research such as described in these examples will provide the basis for techniques allowing student-computer interaction at a voice level which would more closely resemble the familiar student-human teacher interaction.

Given the above brief discussion, the conclusion that techniques allowing verbal interchange in normal conversation language can be developed seems unavoidable. However, much research and development in this area is required. Manual, typed, interaction is already possible albeit in a subset of the natural language. Also the use of AI techniques will allow more flexibility in the student-computerized tutor interaction.

APPENDIX B

DISCUSSION OUTLINE FOR ONR MEETING

Technical Requirements
Instructor Model for Automated Speech
Recognition Based Training Systems

I. Instructor Tasks

A. Design of Curriculum: Instructional decisions regarding curricular design made off-line.

B. Dynamic Decisions during Instruction: On-line decisions regarding instructional alternatives.

II. Off-line Design

A. Overall structure of Curriculum

1. Macro sequencing of concepts
2. Micro schemata to facilitate subsequent performance

B. Design of Manual

C. System Control Questions

1. Display questions--
2. Choice of performance measures
3. Feedback techniques
4. Other miscellaneous training system questions

III. Dynamic Instructional Decisions

A. Establishing schemata (particularly response selection and production.

1. Generative CAI
   a. generation of frames (rules), scenarios (eg.)
   b. CIN based
2. Performance measures
   a. success counters for student model
   b. RT measures for speeded responses on paced skills
   c. diagnostic usage of errors and pauses
3. Feedback
4. Remediation
5. Optimizing algorithms

B. Establishing Paced Skills (Adaptive Training)

1. Break skills into componants: Move one componant from controlled to auto processing before working on next componant? Because of limited resources--performance breaks down in early controlled processing
2. Adaptive Variable(s): Primarily rate?
3. Student Model
4. Performance Measurement: Latency measures; RT on targets, RT on probes. Error measures; errors on distractors and foils. Performance on secondary tasks as resource capacity measure.
5. Optimizing Routines: Solving for optimal switch point from one skill to the next related skill.
6. Cost/Benefit Structure Determination: Transfer considerations etc.

Preliminary Analysis
Auto-Speech Technology Based Training Systems

I. Tasks--In Context

A. Cues

1. Cues are primarily visual: e.g. A radar screen (GCA,AIC) or the actual aircraft (LSO).

2. Some verbal cues: e.g. Verbal responses from approaching aircraft (LSO) or pilot (AIC).

3. Some cues internal: e.g. Temporal cues--certain number of calls per unit time.

B. Response Requirements

1. Verbal responses--All three require this.

2. Motor responses--Only the AIC task requires buttons, foot pedals, etc., to be depressed during operations.

C. Temporal Requirements

1. Unpaced: All require some "unhurried" responding, e.g. accepting a handoff from another controller in GCA-CTS.

2. Paced: Responses are demanded within temporal constraints as required by speed of approaching aircraft.

II. Analysis of Tasks

A. Visual Componants

1. Above threshold

2. Divided displays: Scanning responses required (GCA)

3. Perceptual Cues Subtle: Some perceptual learning required (LSO)

4. Motion (particularly LSO)

B. Auditory Cues

1. Above threshold

2. Background Noise?

C. Temporal Requirements

1. Dual task situation?
Encoding, Search/Comparison, and Response Selection is simultaneous with Response Production (verbal and/or motor) leading to capacity limitation considerations.

2. Encoding
Uncertain about effective cues?
Some cues may be unitized quite early?
e.g. GCA Target, Intersect, Trail combo.

3. Search/Comparison

a) Visual Search: Simultaneous inputs will cause divided attention deficits with controlled processing early in training.
b) Memory Search: Categorical structure of memory set?

4. Response Selection: Internal schemata unknown but could be of considerable extent. Related to linguistic structure of response.

III. Anecdotal Observations

A. "Expert"

1. Notes scanning and processing while verbalizing

2. Rapid scanning of display

3. Unaware of many functions indicating rapid automatic processing

4. Learns expectancies (anticipates)

B. "Novice"

1. Pauses in verbalizations: e.g. "Turn..right.. heading..one......./ /...five...five" indicating degradation of verbal task because of extensive controlled processing.

2. Intrusions of incorrect terminology: Response selection errors could signify several problems, e.g. interrupted processing, incorrect rule structure/schemata?

3. Omissions: Controlled processing not completed in time?

4. Inappropriate scanning responses: Students will stare at small portion of display.

Features:

1. Intersect point
2. Trail angle
3. Range Hashmarks

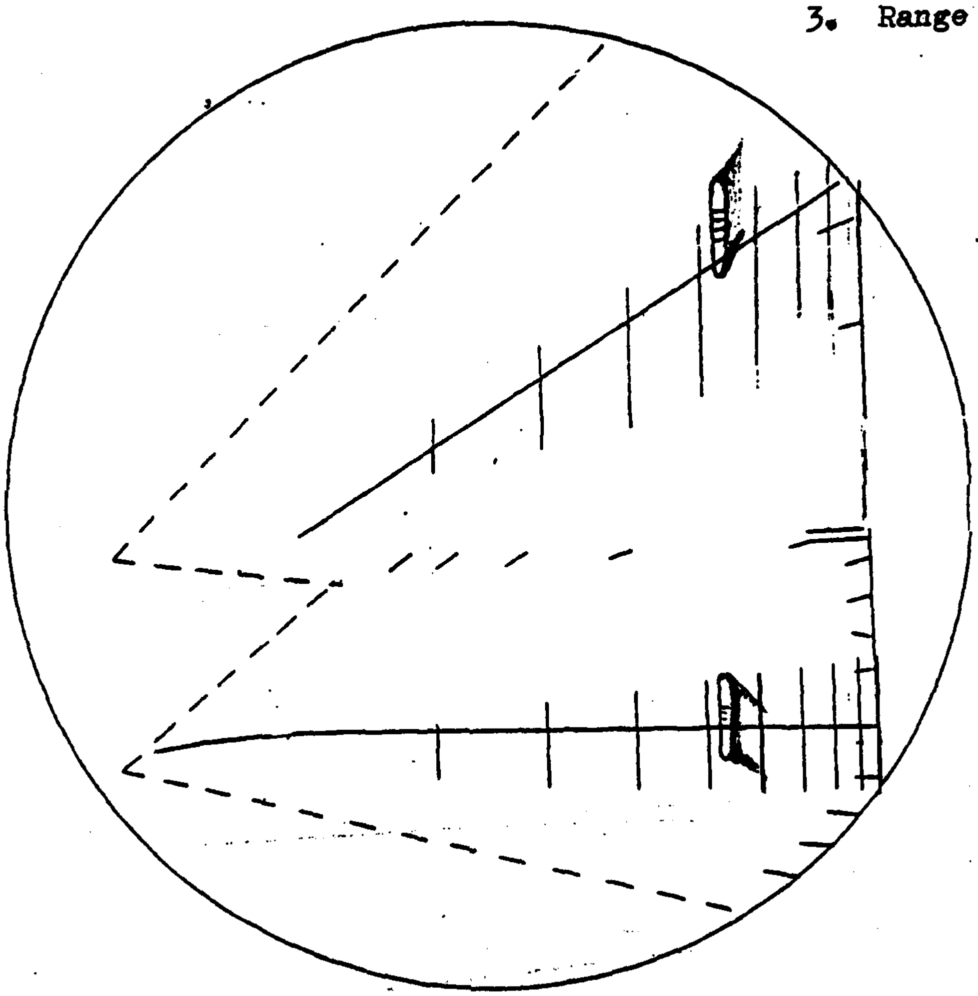

Figure B-1. Example PAR Display

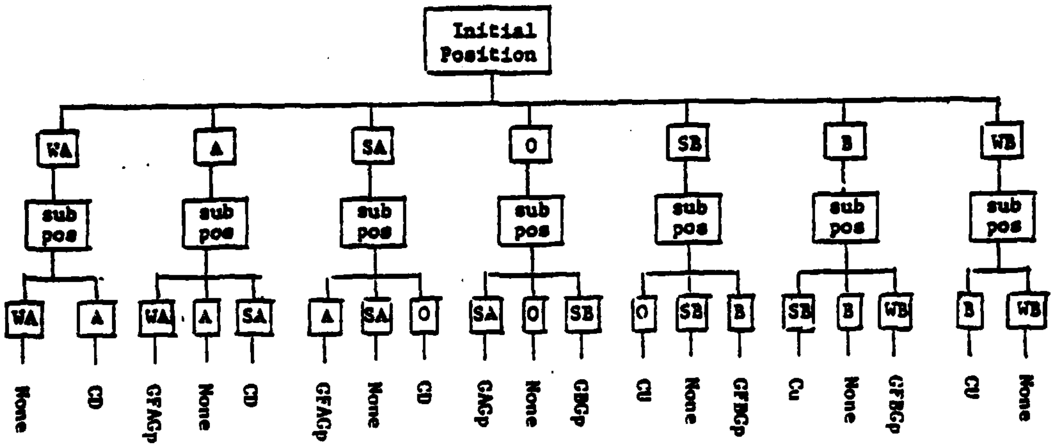

Figure B-2. Trend Calls to be Generated as a Function of Initial and Subsequent Positions.

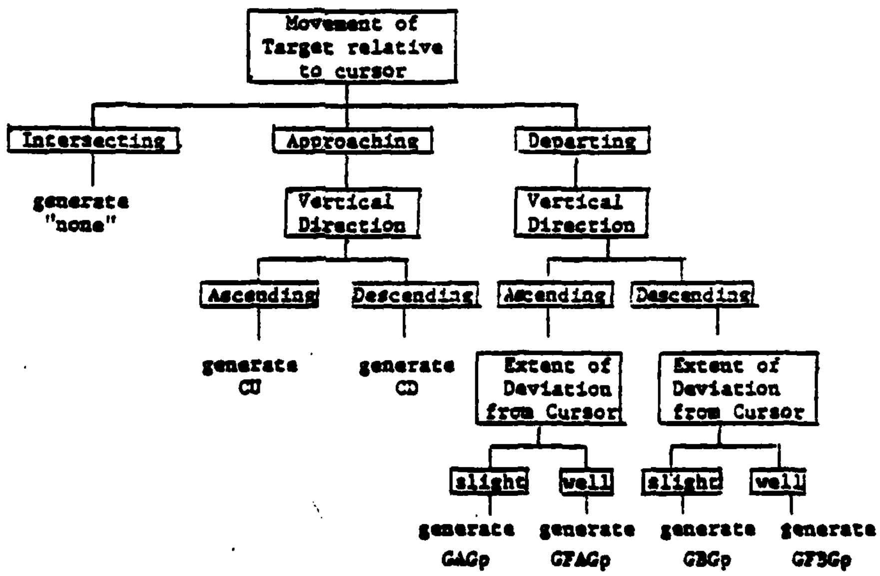

Figure B-3. Trend Calls as a Function of Target Movement.

TABLE B1. ABBREVIATIONS OF THE LIMITED VOCABULARY TO BE USED BY THE TRAINEE

W	well	S	slightly	C	coming	G	going
A	above	O	on	U	up	F	further
B	below	Gp	Glidepath	D	down		

TABLE B-2. VALID POSITION ADVISORIES

well above glidepath	WAGp	slightly below glidepath	SBGp
above glidepath	AGp	below glidepath	BGp
slightly above glidepath	SAGp	well below glidepath	WBGp
on glidepath	OGp		

TABLE B-3. VALID TREND STATEMENTS BASED ON OLD AND NEW POSITIONS

Old Position	New Position	Trend Statement	Old Position	New Position	Trend Statement
WAGp	WAGp	None	OGp	SBGp	GBGp
WAGp	AGp	CD	SBGp	OGp	CU
AGp	WAGp	GFAGp	SBGp	BGp	GFBGp
AGp	SAGp	CD	BGp	SBGp	CU
SAGp	AGp	GFAGp	BGp	WBGp	GFBGp
SAGp	OGp	CD	WBGp	BGp	CU
OGp	SAGp	GAGp	WBGp	WBGp	None

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